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The application of machine learning to forecast stratus burn-off

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THE APPLICATION OF MACHINE LEARNING TO FORECAST STRATUS BURN-OFF

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ABSTRACT

THE APPLICATION OF MACHINE LEARNING TO FORECAST STRATUS BURN-OFF

By George Astrop Fenton III

Stratus occurs regularly over the San Francisco Bay Area from late spring to early fall and is a primary cause of delays at San Francisco International Airport. A database of meteorological measurements has been accumulated from around the Bay Area by the Marine Stratus Initiative, which endeavors to provide forecast guidance to optimize airport capacity for arriving flights. A data set derived from this database will be analyzed using the See5 machine learning system to create an algorithm for one-hour real-time forecasts of Bay Area stratus burn-off. This thesis will demonstrate machine learning analysis as a practical tool for operational forecasting of stratus burn-off. This research indicates a twofold benefit in applying these methods. Operationally, the algorithm is capable of properly forecasting up to 80% of the burn-off cases. Diagnostically, the analysis identified 10 meteorological variables and corresponding threshold values key to stratus burn-off over the San Francisco Bay.

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1. INTRODUCTION

During the summer season over the San Francisco Bay Area, episodes of marine fog and stratus are typical on a diurnal cycle. The stratus ceiling over the San Francisco Bay frequently impacts San Francisco International Airport (SFO) by reducing the incoming flight capacity of the airport below its demand. The stratus cycle is a complex interaction of local geography, diurnal sea breeze circulation, subsidence inversion, cloud physics and radiation.

The occurrence and dissipation of fog and stratus has been one of the most intractable problems in meteorology (Glahn & Lowry 1972). The application of machine learning analysis to the stratus burn-off process may yield an alternative algorithm specific to the process that may provide real-time forecast guidance. The goal of this research is to provide a one-hour real-time forecast of stratus burn-off.

Machine learning (ML) is an artificial intelligence method that recognizes patterns in empirical data specific to the process and uses those patterns to forecast future occurrences. The results of machine learning analyses are computationally simple with minimal data assimilation required and would be well suited for operational application. ML analysis is objective in selecting variables and corresponding threshold values, although attribute and case selection are subjective processes dependent upon the skill of the user. The results of a ML analysis are comprehensible and logical to the user.

Most physical meteorology models are developed using analogs to known physical processes, and their performance is evaluated against cases with known conditions and outcomes (process from general to specific). A machine learning model is conversely built by analyzing cases and defining an analog for the process (process from specific to general). Either approach is still evaluated against cases with known conditions. The stratus problem may be well suited to a machine learning approach since it is defined by processes specific to the San Francisco Bay. The results of the See5 analysis will be specific to the Bay Area stratus burn-off process.

The Marine Stratus Initiative (MSI) (Clark & Wilson 1996; 1997) is an effort to develop an algorithm for a probabilistic short-term (less than 6 hour) forecast of stratus burn-off time on approach to San Francisco International Airport to aid in optimizing airport capacity during stratus episodes. The MSI has archived an extensive database of meteorological observations from around the San Francisco Bay Area to support development of the algorithm.

Tag and Peak (1996) applied the C4.5 machine learning system (Quinlan 1993) to forecast the occurrence of marine fog along the California coast. Their results indicated sun angle, inversion base height, differential between dewpoint and sea surface temperature, wind speed, inversion strength and presence of a marine inversion as key variables for forecasting marine fog and haze. The similarity of the meteorological processes involved between California coastal fog and San Francisco Bay Area stratus merit the consideration of C4.5 analysis as a potentially useful and innovative approach to forecasting Bay Area stratus burn-off and is the objective of this thesis.

Data sets derived from the MSI archive, corresponding to stratus burn-off events, will be analyzed using the See5 machine learning system (See5). See5 will process the data sets using induction (generalization of patterns from specific data) and probabilistic analysis, and determine the meteorological conditions that correlate to stratus burn-off, to provide objective forecast guidance for Bay Area stratus burn-off.

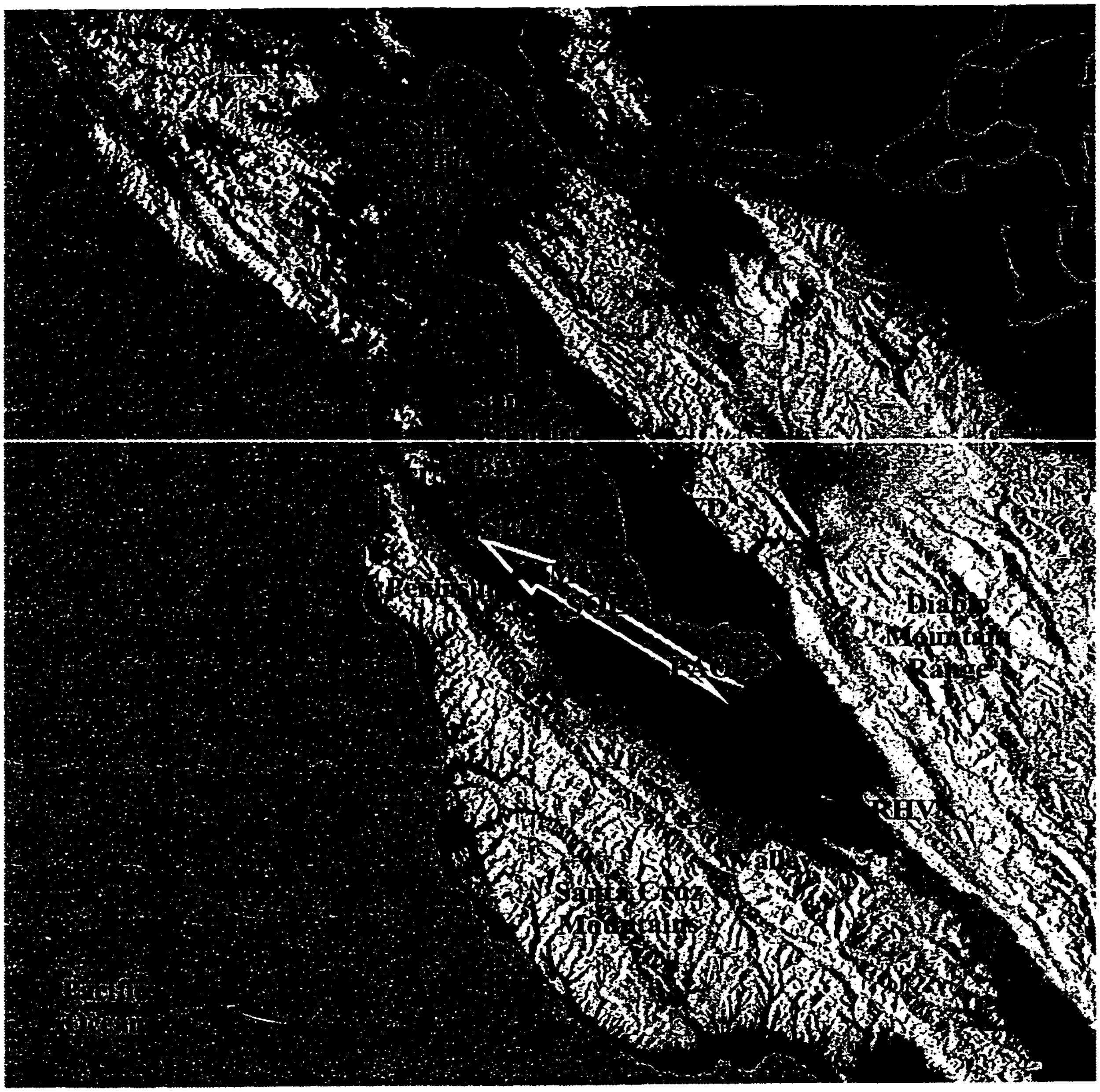
2. STRATUS

Fog and stratus exists along the California coast within the neutral marine boundary layer (MBL) below a capping inversion created by warm, subsiding air from a semi-permanent, summertime, subtropical Pacific High blowing over cold upwelling coastal water (Pilie et al. 1979, Leipper 1994, Clark & Wilson 1996). The stratus has a consistent vertical structure, with heat and moisture interacting in a quasi-closed system. Stratus is typically present during 1/3 of the days from May to September, the "stratus season" (Leipper 1994, Keller 1997).

The large-scale wind circulation creates conditions favorable to stratus formation over the NE Pacific controlled by the Pacific High. This circulation creates southward flow along the coast, causing cold upwelling (with sea surface temperatures, SST, typically in the mid-50°F range) in the Pacific Ocean along the California coast (Clark & Wilson 1997). The Pacific High produces a strong subsidence inversion, with warm dry air capping cool, moist (MBL) air below (Pilie et al. 1979).

The geography of the San Francisco Bay Area (Figure 1) plays a key role in the stratus cycle creating boundary and initial conditions specific to the stratus cycle of the Bay Area. The San Francisco Bay is at the northwest end of the Santa Clara Valley. The Peninsula and Santa Cruz Mountains separate the Santa Clara Valley and the San Francisco Bay from the Pacific Ocean. These coastal mountains block incursion of marine air when the subsidence inversion base is lower than 1500 feet, with several gaps

Figure 1. San Francisco Bay Area.
Bay Area geography including the San Francisco Bay, Santa Cruz Mountains, Diablo Mountain Range, Santa Clara Valley and the Pacific Ocean. The 3-letter names represent meteorological surface stations (see Table 3) and their locations relative to San Francisco International Airport (SFO). The white arrow indicates the aircraft approach path into SFO.



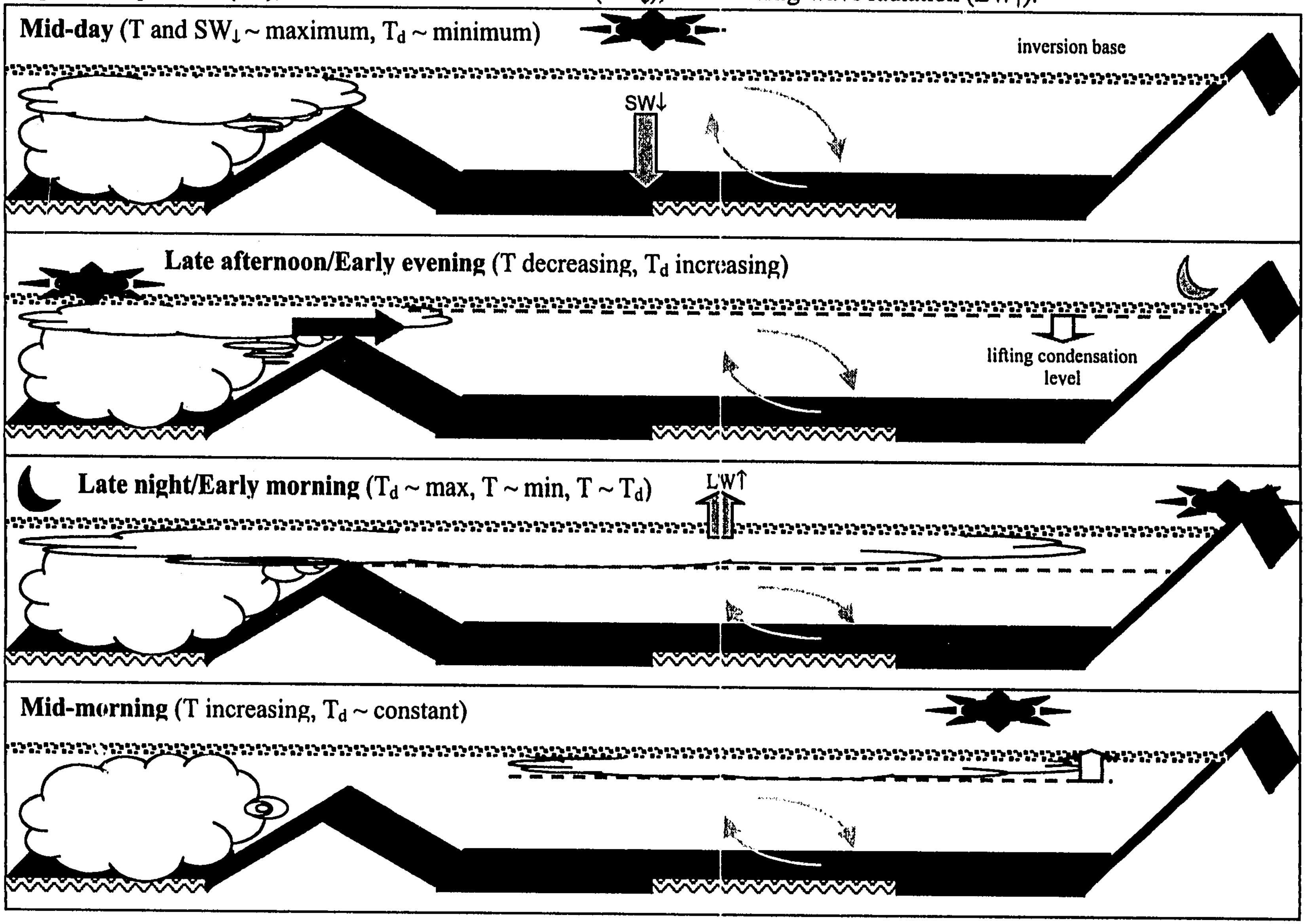
in the coastal mountain range that allow cool, moist air advection into the Bay Area even if the inversion base is lower than the mountain tops. These gaps include the San Bruno Gap west-northwest of SFO, the Crystal Springs Gap south-southwest of SFO, and the Golden Gate north-northwest of SFO. On-shore advection of marine air is the primary moisture source for the Bay Area. The San Francisco Bay may provide a supplemental source of moisture within the Bay Area due to evaporation during daytime heating. East of the Bay Area, enclosing the valley is the inland Diablo Range. The inland and coastal mountains help to confine cool, moist air within the Bay Area.

Within the MBL, a regional scale diurnal sea-breeze circulation occurs, which contributes to the diurnal stratus cycle over the Bay Area (Figure 2). The effects of MBL heating and cooling may be complicated by thermal advection from the daily sea-breeze circulation and drainage flows. Changes in local winds may significantly influence timing of the stratus cycle (Clark & Wilson 1997).

2.1. LCL and the Inversion

Fog and stratus processes combine cloud physics, micrometeorology, boundary layer meteorology and mesoscale meteorology (Cotton & Anthes 1989). Jiusto (1981) identified a number of factors relevant in general to fog and stratus processes that reflect this combination, with the following factors specifically applicable to Bay Area stratus process. Surface radiative heating of the well mixed boundary layer below the stratus raises the lifting condensation level (LCL) and stratus base. Raising of the LCL is counter productive (providing "negative forcing") to cloud growth or maintenance. Moist air cooling at the stratus top by radiative flux divergence lowers the LCL. Lowering the

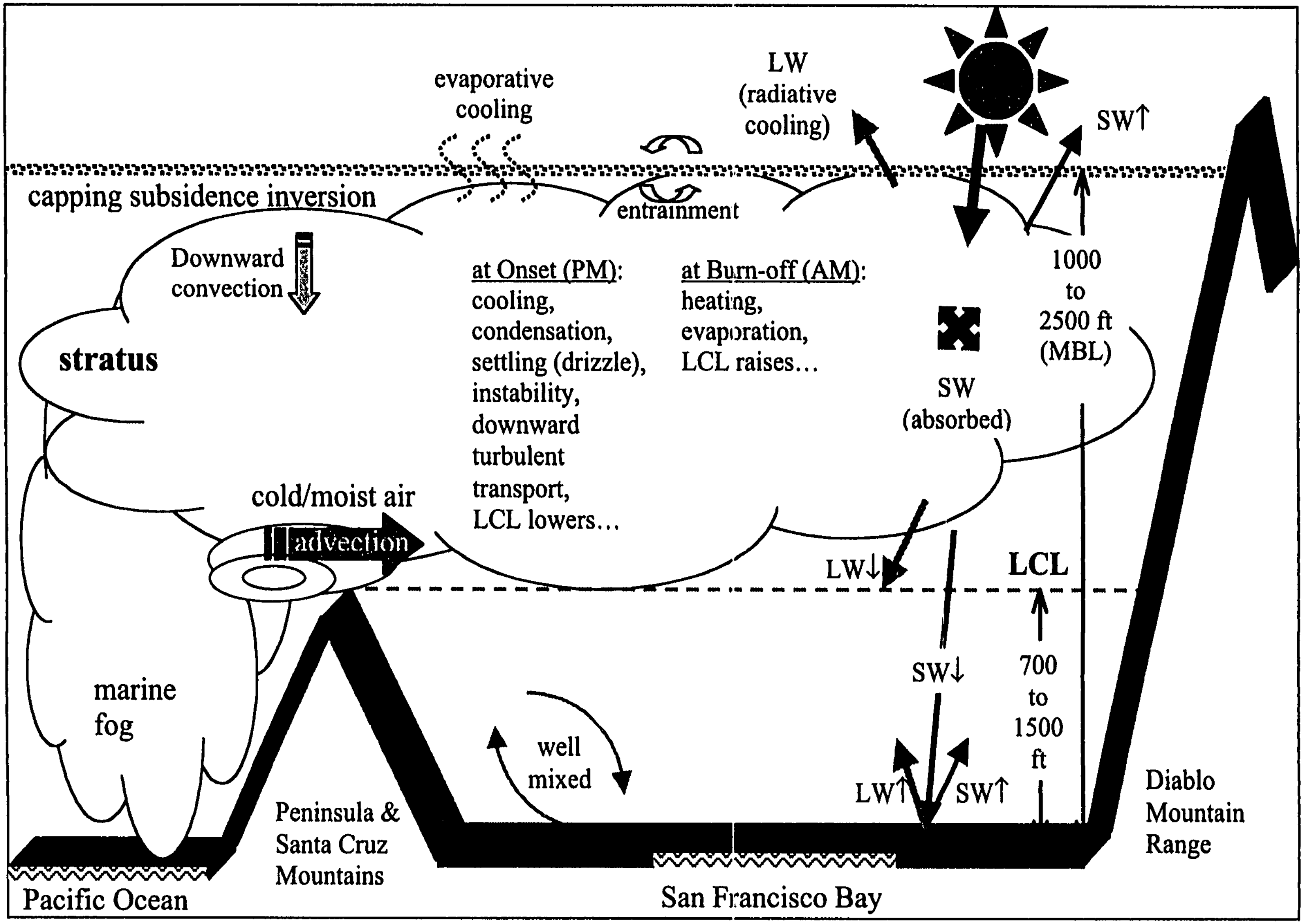
Figure 2. The diurnal stratus cycle of the San Francisco Bay (Clark and Wilson 1997). Caption symbols: temperature (T), dewpoint temperature (T_d), incident short-wave radiation ($SW_\downarrow$), emitted long-wave radiation ($LW_\uparrow$).



LCL is conducive (providing "positive forcing") to cloud growth or maintenance. Vertical fluxes of heat and moisture, with downward fluxes of cool moist air through the cloud causes the LCL to lower, and upward fluxes of warm, dry air through the boundary layer below the cloud causes the LCL to rise. During the stratus cycle, turbulent kinetic energy (TKE) is greatest within the cloud during the night and has a vertically uniform profile from the surface to the cloud top during the day (Cotton & Anthes 1989). Horizontal advection of moist, cool air into the Bay Area from the coast (on-shore sea-breeze) contributes to lowering of the LCL, and advection of warm, dry air into the Bay Area from the valley (off-shore land-breeze) contributes to raising the LCL. Air drying by subsidence forms a capping inversion over the MBL.

Sounding data indicate sharp changes in potential temperature and total water mixing ratio at the inversion (Paluch & Lenschow 1991). At the stratus top (inversion base), incoming solar radiation and entrainment of the warmer inversion air evaporate droplets from the cloud top (Figure 3) (Pilie et al. 1979), maintaining an equilibrium between the heating and cooling effects. The cloud top is maintained at dewpoint by the cooling effects of latent heat of droplet evaporation, flux divergence of cloud top long-wave radiation and mixing within the MBL. These processes maintain a low temperature at the base of the inversion, while the subsiding air maintains a higher temperature at the top of the inversion, creating a stable inversion that caps the neutral MBL below. A significant fraction of the long-wave radiative cooling at the cloud top is offset by subsidence warming, with the consequent lapse rate reduction reducing upward heat flux in the cloud and buoyant production of turbulence (Cotton & Anthes 1989).

Figure 3. Structure and processes governing the San Francisco Bay stratus cycle (Pilie et al. 1979).



The inversion must exist for fog/stratus to exist otherwise low level moisture will disperse (Paluch & Lenschow 1991). The inversion base height determines the mass of air to be heated (Clark & Wilson 1997). The base of the inversion caps the stratus cloud, with the cloud top/inversion base typically ranging from 1000 to 2500 feet (Clark & Wilson 1997). The LCL defines the cloud base height, which typically ranges from 700 to 1500 feet (Clark & Wilson 1997). The strength of the inversion limits entrainment from above the MBL. The MBL has enough TKE to quickly distribute heat and moisture vertically through the entire MBL, making it well mixed. Marine fog along the California coast persists within the MBL, due to warm, moist, offshore air cooling and condensing (with the LCL lowering below the inversion base) as it passes over the cooler upwelling water near the coast.

There are several mechanisms on several meteorological scales that cause short-term changes to inversion base height (Clark & Wilson 1996), thus influencing the timing of stratus burn-off. Synoptic scale troughs raise inversion heights on approach and lower heights upon passage. The inversion height also depends upon the strength and location of the Pacific High. Variations in the large-scale pressure field (i.e. surface fronts, pressure troughs, vorticity maxima) and associated vertical motions influence changes in inversion strength and height, and MBL depth.

On a regional (or synoptic) scale, gravity waves may produce high frequency, low amplitude variations in inversion base height, which may impact stratus burn-off time on the scale of an hour. Gravity waves in the stable layer above the inversion are induced by horizontal inhomogeneities of air density in the cloud layer, which in turn induce oscillations in MBL height and support vertical transport of heat and moisture within the cloud (Paluch & Lenschow 1991). The induced transport mixes warm, dry subsidence air and cool, moist MBL air, evaporating the stratus and increasing the rate of burn-off. The density gradient at the top of the MBL provides an ideal boundary for gravity wave ducting.

On a local scale (encompassing the Bay Area), surface wind divergence due to the combined effects of local winds and topography below the stratus can lower the inversion base. When local winds are offshore, the stronger the winds, the higher the air temperature, and usually the lower the inversion base height (Leipper 1994).

2.2. Stratus Cycle

A necessary and sufficient condition for stratus burn-off is that the LCL is at or above the height of the inversion base, due to either the LCL rising and/or the inversion base lowering. For stratus onset the converse of the LCL lowering below the inversion base is a necessary, but not sufficient condition. For onset there must also be sufficient TKE to lift air parcels to the LCL.

Stratus onset typically occurs in the evening or early morning following the afternoon onshore sea-breeze advection of moist cool air from the ocean and radiative cooling of the MBL, lowering the LCL below the inversion base. Stratus burn-off or dissipation typically occurs in the late morning when the MBL is sufficiently heated to evaporate the liquid water of the stratus deck and raise the LCL above the inversion base (Clark & Wilson 1997).

2.2.1. Stratus Onset

Components of the stratus onset process include onshore advection of cool, moist marine air during the afternoon sea-breeze coupled with late afternoon/early evening cooling of the MBL dropping the LCL below the inversion base height. TKE raises MBL air above the LCL, with water vapor in the MBL air between the LCL and inversion base condensing to cloud droplets. LW radiation emission from the top of the stratus, promotes cooling and condensation of the air at the top of the MBL and increases upper MBL instability. The stratus base (LCL) propagates downward (lowers) as the MBL continues to radiatively cool, destabilizing the stratus, propagating downward fluxes of stratus and inducing upward fluxes of MBL water vapor below the stratus up to the base of the stratus (Cotton & Anthes 1989). Such processes would not require drizzle to moisten the air, but drizzle typically occurs in the upper levels of stratus over the Bay Area (Goodman 1977).

2.2.2. Stratus Burn-off

Burn-off occurs when enough heat is received to heat the MBL and evaporate all the liquid water in the cloud. Sufficient daytime heating and stratus mixing with subsiding air may initiate stratus burn-off. Key components and conditions specific to the Bay Area stratus burn-off process include solar radiation at the surface and subsequent warming of the MBL by surface sensible heat fluxes (long-wave radiation) (Keller 1997). Some absorption of incident short-wave radiation by the cloud heats the upper MBL air. Vertical mixing of warmer, drier MBL air up to the stratus base and horizontal advection of drier, warmer inland air induces heating and drying of the MBL. This subsequently raises the LCL level and stratus evaporates from the cloud base. Stratus burn-off is complete when the LCL is greater than or equal to the inversion height.

In addition to stratus burning off by the vertical processes described, the stratus may burn-off horizontally from the edges due to the topography of the Bay Area. The outer edges of the Bay Area stratus are near the mountains encircling the Bay. The eastern slopes of the Santa Cruz and Peninsula Mountains absorb more SW radiation, earlier than the valley floor and their surfaces may emit LW radiation sooner and closer to the stratus base than the valley floor and western slopes of the Diablo Range. This may accelerate stratus burn-off at the western edges of the valley. Motions due to horizontal density differences across the cloud and clear air interface contribute to velocity fluctuations, moving cloudy air down and under clear air, which may erode the cloud from the edges and dissipate the stratus by mixing (Paluch & Lenschow 1991). Also, since the San Francisco Bay is at the center of the valley, more of the absorbed SW may be converted for evaporation of the bay water than emission as LW, increasing moisture, decreasing heating and thus inhibiting burn-off over the Bay itself.

3. MACHINE LEARNING

3.1. Artificial Intelligence

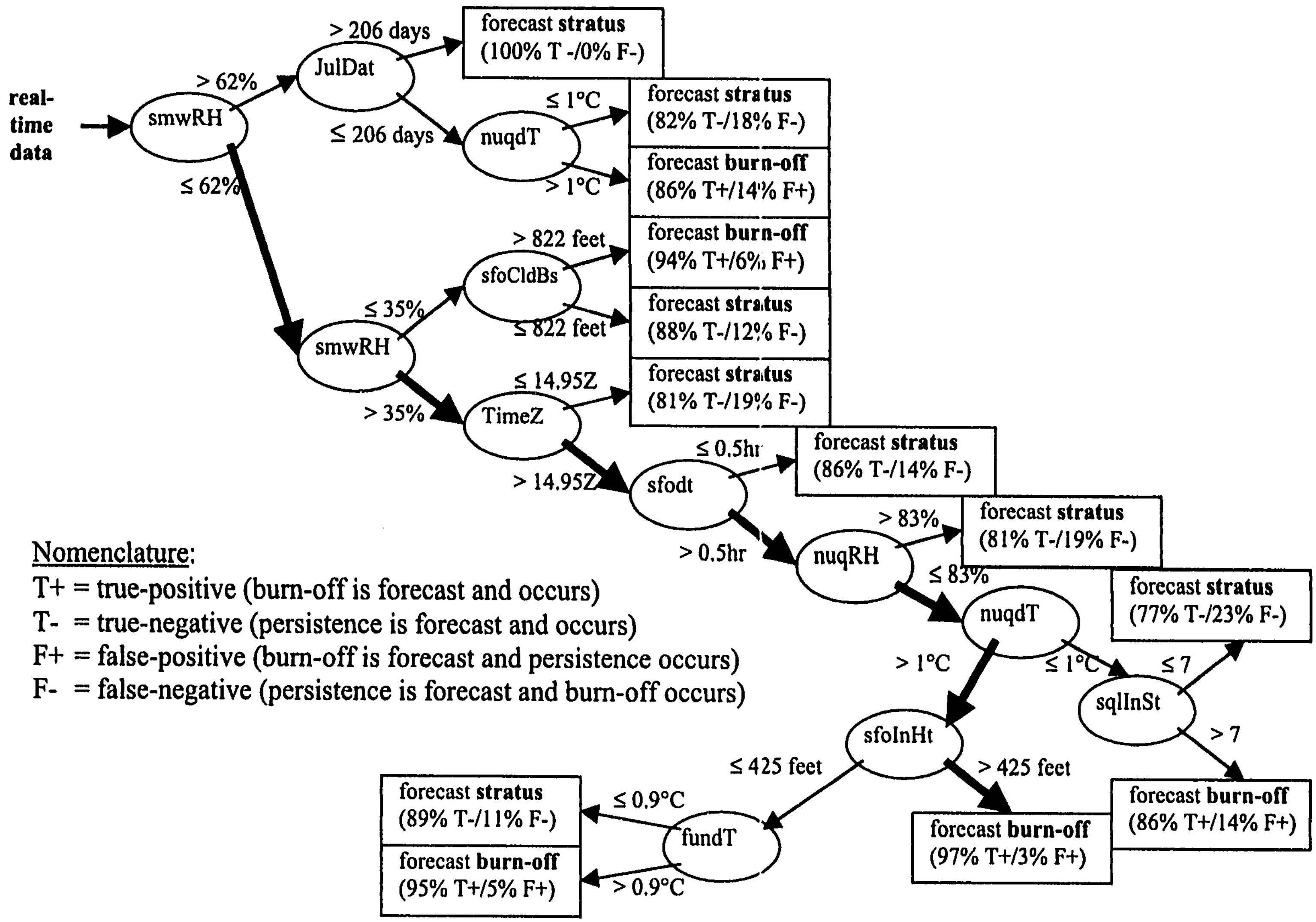
Machine learning is an artificial intelligence method. Artificial intelligence (AI) techniques provide objective, computational analysis methods that infer patterns in data which may be applied to predict or recognize future cases. The performance of AI methods relies upon initial selection of appropriate and representative variables that have sufficient and accurate data, using specific knowledge of the processes and conditions being analyzed, for unambiguous cases (Weiss & Kulikowski 1990). Meteorology lags behind other fields in employing AI technologies, and has special requirements in having to integrate diverse knowledge types, and in its need to represent time, space and uncertainty levels (Moninger & Cote 1987). Machine learning objectively determines patterns defining a process by applying error reduction methods to a training data set of known cases and conditions representative of the process being evaluated. One of the motivations for developing ML methods is to represent solutions in formats that are easily understood and compatible with human reasoning.

3.2. See5

The work of Tag and Peak (1996) was the impetus for applying machine learning to the stratus problem. Tag and Peak used the C4.5 machine learning system to classify and forecast maritime fog and haze formation and dissipation along the California coast. They evaluated data sets from weather ship observations and buoys off the California coast. The principal variables chosen by their analysis for forecasting maritime fog and haze were sun angle, wind speed, inversion height and strength, relative humidity and barometric pressure. The C4.5 generated forecast rules or decisions were reasonable, demonstrating that objective induction can reveal physical processes directly from data. Tag and Peak were able to successfully identify marine fog versus clear conditions for 71% of 183 cases they tested, which was better than a persistence forecast of 47%.

Quinlan (1993) developed the See5 (1998) machine learning system as a tool for data mining, or extracting patterns from stored data. The See5 program analyzes data and generates a classifier or classification model in the form of a decision tree (Figure 4)

Figure 4. Stratus burn-off forecast decision tree (DT) from the See5 analysis of the training data set.
Refer to Tables 3 and 4 for explanation of variable names. (Note: Decisions are elipses and forecasts are rectangles. The DT path indicated in bold arrows corresponds to 68% of the burn-off training cases.)



Nomenclature:

T+ = true-positive (burn-off is forecast and occurs)
T- = true-negative (persistence is forecast and occurs)
F+ = false-positive (burn-off is forecast and persistence occurs)
F- = false-negative (persistence is forecast and burn-off occurs)

and/or rule set (Figure 5). A classification model describes the traits (variables and corresponding threshold values) of a class (a specific object or process). An example of a simple classification model for classifying an orange is if an object has the traits of being a fruit, round, orange and bigger than a tennis ball, but smaller than a softball, the object would be classified as an orange. Quinlan (1993) established the following criteria for applying C4.5 (and See5) to a classification problem: A case must be describable as a fixed collection of variables (attributes) (i.e. the classification or identification of a fruit may be based upon such attributes as the color, shape, size of the fruit). All classes must be sharply delineated (e.g. an apple cannot be confused as an orange, but a tangelo may be difficult to differentiate from a tangerine). There must be sufficient data (enough cases corresponding to a class to evidence a pattern, and enough attributes to build a pattern representative of the class). The process must be suitable for expression as logical classification models in the form of decision trees or rule sets.

See5 allows the user to select the output of the analysis in the form of a decision tree (DT) or as a rule set (RS). Analysis of the stratus problem will utilize both DTs and RSs. This process will help to identify if either method is superior in forecasting stratus burn-off.

3.2.1. Decision Trees

A DT consists of leaves and branches (Figure 4). A branch is a single decision or test on an attribute value (e.g. is San Mateo relative humidity (smwRH) > 62%?). A root is a starting decision (e.g. if the case being evaluated has a value for smwRH ≤ 62% it will follow the branch to another decision asking if smwRH > 35%, if it has a smwRH > 62%

Figure 5. Stratus burn-off forecast rule set (RS) from See5 analysis of the training data set. Refer to Tables 3 and 4 for explanation of variable names. (Note: The accuracies indicated are based upon apparent error, for this analysis true error on average (see Table 1) is approximately 17.4% greater than apparent error.)

Stratus burn-off forecast rules -
(a stratus (persistence) forecast is a negative forecast, and a burn-off (change) forecast is a positive forecast):

Forecast Rule 1: (corresponds to 19% of the training data cases)
If, smwRH > 35%,
then, forecast **stratus** [95% true-negative/5% false-negative].

Forecast Rule 2: (corresponds to 6% of the training data cases)
If, sqlInSt ≤ 7, and
nuqdT ≤ 1°C,
then, forecast **stratus** [93% true-negative/7% false-negative].

Forecast Rule 3: (corresponds to 5 % of the training data cases)
If, nuqRH > 83%, and
smwRH ≤ 62%,
then, forecast **stratus** [92% true-negative/8% false-negative].

Forecast Rule 4: (corresponds to 11% of the training data cases)
If, sfoCldBs ≤ 822 feet, and
smwRH ≤ 35%,
then, forecast **stratus** [92% true-negative/8% false-negative].

Forecast Rule 5: (corresponds to 6% of the training data cases)
If, TimeZ > 14.95Z, and
sfodt ≤ 0.5 hours,
then, forecast **stratus** [87% true-negative/13% false-negative].

Forecast Rule 6: (corresponds to 14% of the training data cases)
If, TimeZ ≤ 14.95Z, and
smwRH > 35%,
then, forecast **stratus** [87% true-negative/13% false-negative].

Forecast Rule 7: (corresponds to 5% of the training data cases)
If, sfoInHt ≤ 425 feet, and
fundT ≤ 0.9°C,
then, forecast **stratus** [67% true-negative/33% false-negative].

Forecast Rule 8: (corresponds to 63% of the training data cases)
If, smwRH ≤ 62%,
then, forecast **burn-off** [64% true-positive/36% false-positive].

Default Rule: (corresponds to 3% of the training data cases)
If, none of the above rules are satisfied,
then, forecast **burn-off**.

it will follow the branch to the decision asking if the Julian Date of the case (JulDat) > 206 days). If a case satisfies a specific sequence of conditions through the decision tree that ultimately arrives at a terminal node or leaf, the case is classified as a member of the class defined by the leaf. As an example, if a case satisfies the conditions defined by the path of bold arrows through the DT in Figure 4, it would be classified or forecast as a burn-off case.

A DT is induced by iterative selection and subdivision of variables from training cases that correlate to the conditions or classes being classified. An entropy function is used to define the threshold values for the selected variables by tuning a classifier decision (i.e. adjusting the value to remove cases that do not correspond to a class for the given variable). The entropy function is capable of inferring a pattern from data when the complete population or distribution of the data is not available. The entropy function used by See5 is based upon Bayes Rule.

Bayes Rule (Quinlan 1993) is a statistical method of error reduction and defines the conditional probability calculation,

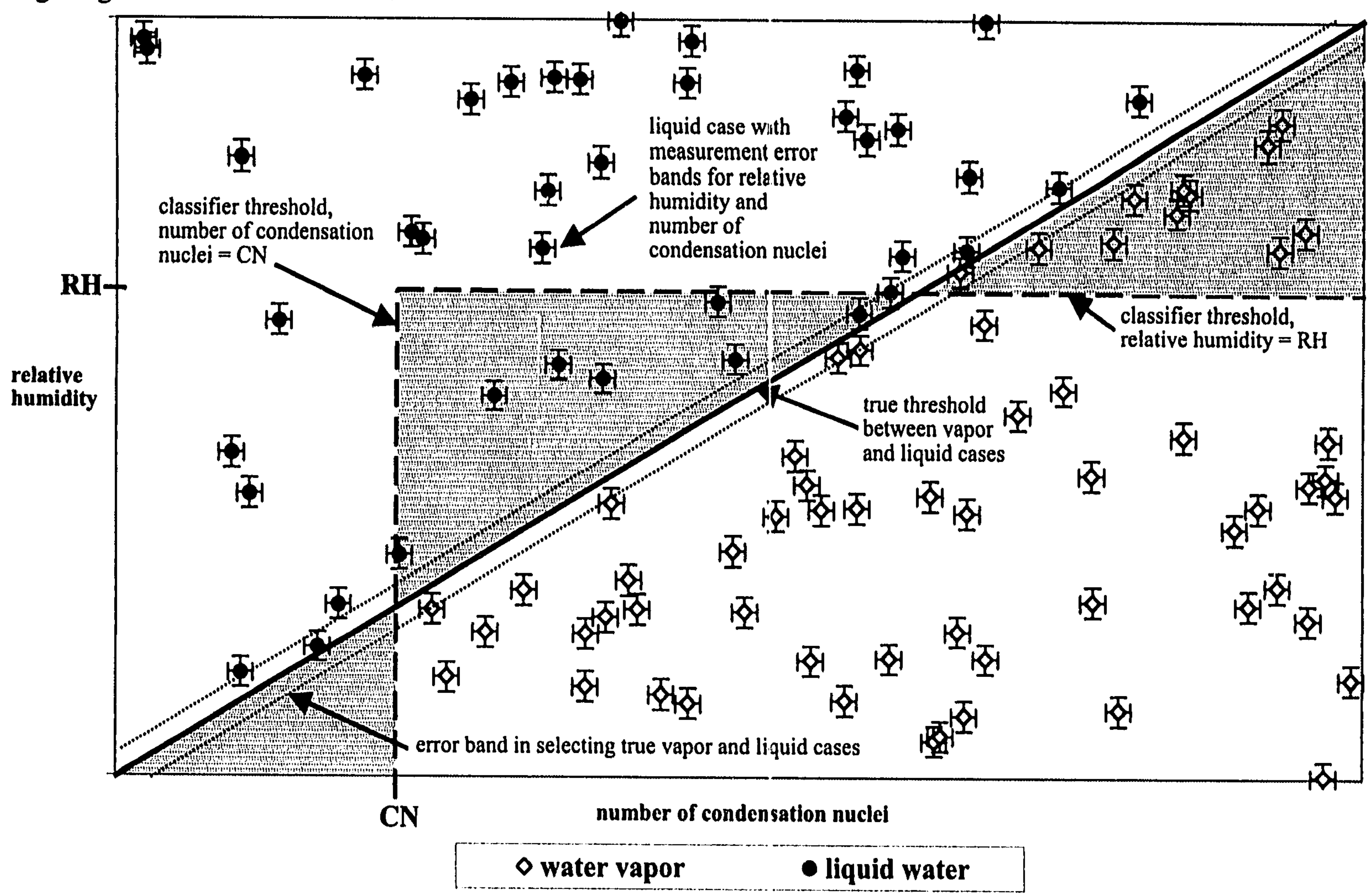
$$P(C|e) = [P(e|C)P(C)]/P(e) \tag{1}$$

P = probability
C = class (i.e. stratus burn-off)
e = pattern of evidence (i.e. smwRH < 62%)
P(C|e) = probability of class, C, as a function of the pattern of evidence, e
P(e|C) = conditional probability of the pattern of evidence, e, for a given class, C
P(C) = probability of class, C
P(e) = probability of pattern of evidence, e.

Since classes may be known (i.e. burn-off time), a pattern may be related to a given class (P(e/C)). In order to predict a class (i.e. burn-off) as a function of a pattern of evidence (i.e. relative humidity), the class must be defined as a function of the pattern. Equation (1) effectively inverts the pattern (a variable, smwRH, defined as a function of a class, burn-off condition) to create a predictive function (a class defined by a variable, or burn-off condition as a function of smwRH).

The value of the pattern of evidence, e, (i.e. smwRH < 62%) from Equation (1) represents a threshold value for a given variable. An example of a threshold value would be no stratus if the LCL is greater than the inversion height. Variables relevant to the class or condition are referred to as "attributes". An example of an attribute specific to the stratus problem would be the LCL or inversion base height. For a problem with n attributes, the separating surface between classes is a (n-1) dimensional hyperplane in an n-dimensional Euclidean description space (Figure 6). The separating surfaces are threshold values for the given variables on the given planes. Figure 6 demonstrates a 2-dimensional description space defining cases with water in vapor or liquid form, as a function of relative humidity and the number of condensation nuclei. The error bands around the data points represent the uncertainty in the values of the relative humidity and number of condensation nuclei for each data point, which may be attributable to measurement error, etc. The band about the true threshold represents the uncertainty or error in assigning a training case to the correct class as a liquid or vapor case. The vertical dashed line represents the threshold value, CN, for condensation nuclei. The horizontal dashed line represents the threshold value, RH, for relative humidity. For the classification model defined in Figure 6, cases with relative humidity less than RH and number of condensation nuclei greater than CN would be classified as water vapor and all

Figure 6. A 2-dimensional Euclidean description space defining water vapor and liquid water cases. With classifier thresholds at relative humidity < RH and number of condensation nuclei > CN, 49 of 60 (82%) of the vapor cases and 36 of 40 (90%) of the liquid cases would be properly classified. The shaded regions are misclassified using the given classifier thresholds.



other cases would be classified as liquid water. The cases falling within the shaded regions would be incorrectly classified by the classification model.

Pruning is an approach utilized to limit decision tree growth and avoid overfitting. Overfitting a classifier occurs when a classifier defines decisions or rules that are specific to the training data but not general to the patterns in the data. Training data are a set of cases with known outcomes and known attribute values that are used by the machine learning code to build a classification model. If a classifier has 100 training cases and fits the cases with 100 leaves or rules, the classifier has overfit the data and is unlikely to accurately predict unseen test cases. Pruning removes parts of the tree that do not contribute to classification accuracy on unseen cases, preventing a tree that infers more structure than is justified.

See5 is capable of analyzing cases with missing data, which is valuable when analyzing real world data. Discarding cases with missing data is undesirable since it weakens the ability of the system to find patterns. An attribute value may be designated "?" if it is unknown or irrelevant. A large percentage (20%) of the MSI database, for the applicable episodes and conditions was missing data, requiring the substitution of "?".

3.2.2. Rule Sets

A Rule Set (RS) (Figure 5) is an alternative representation of a decision tree classification model that describes the paths through a decision tree as a set of conjunctive (using IF, AND, THEN statements) rules. In Figure 5, Forecast Rule 4 is equivalent to the decision path through the DT in Figure 4 satisfying SFO cloud base height (sfoCldBs) $\leq$ 822 feet, and smwRH $\leq$ 35%, and forecasting that stratus will persist.

Rule sets are potentially more predictive than decision trees since they generalize the decisions in decision trees by removing decisions specific to the particular cases in the training data, without removing those that make up the general patterns in the process or condition being classified. The over-specification (or overfitting) to training cases by a DT may define a process more specifically than necessary (Quinlan 1993), whereas a rule can be generalized, by deleting superfluous conditions, without affecting its predictive accuracy. If a case satisfies all of the conditions stated by the rule, the case is assigned to the class represented by the rule.

In See5, each rule set consists of: one or more rules (e.g. in Figure 5 the RS is comprised of 8 rules), a class predicted by each rule, a value between 0 and 1 (or 0 and 100%) indicating prediction confidence for each rule, and a default classification. A default classification is defined for each RS for when none of the rules in the RS applies to a given case. In Figure 5, these confidence levels are represented by the percent true-positive (burn-off is forecast and verifies) or true-negative (persistent stratus is forecast and verifies) values following each rule. When a RS is used to classify a case, several of the rules may be applicable (all their conditions are satisfied). If more than one rule applies to a case, the rule with the highest confidence value is chosen as the final prediction.

3.2.3. Classifier Performance and Error Rates

With meteorological forecasting, the performance of a forecast method is based upon its skill or ability to forecast versus other methods such as persistence or climatology. The predictive accuracy of a classifier constructed from training cases can be estimated by its performance with test cases (Quinlan 1993). The objective of ML is to build a classifier with the lowest true error rate (i.e. minimize the number of missed forecasts), by finding the best fit to the training data without overfitting the data. True error rate, is the error rate of a classifier on the entire population of cases, which includes all future cases (Weiss & Kulikowski 1990). For ML methods this performance is measured by classifier error rate. Error rate is the proportion of misclassified (misforecasted) cases to all cases being classified (forecasted). The apparent error of the classifier is the error of classifying training data, but not its true error for unseen cases, which will be higher.

The most accurate estimate of true error rate may be achieved by using resampling, which is particularly true for data sets with limited samples. Resampling methods allow training and testing with the same data while still providing nearly unbiased estimates of true error rate. The ten-times cross validation resampling method has been found to provide error rates that accurately represents the true error rate of the classifier (Quinlan 1993, Weiss & Kulikowski 1990), and is thus a preferred resampling method. In ten-times cross validation, a data set is randomly divided into 10 data subsets of equal size and class distribution. Each subset is in turn held out and tested against a classifier trained from the 9 other data subsets. The outcome is ten sets of errors, whose average is representative of the true error of a classifier built with all of the data.

3.3. Machine Learning Applied to the Stratus Problem

The goal of the stratus classification process is to forecast a change from the stratus (persistence) to the clear condition. For the application of machine learning to the stratus problem false-positive and false–negative forecasts are used to measure forecast performance of the See5 generated classification model. An indication other than the current (stratus) condition is a positive forecast for burn-off. A forecast of persistence (continued stratus) is a negative forecast. A "false-negative" occurs when stratus clears within an hour of a forecast for persistent stratus (no burn-off). A "false-positive" occurs when a prediction is made that stratus will clear within an hour and stratus persists. A "true-positive" occurs if clearing is correctly forecast to occur within an hour, and a "true-negative" occurs when persistence or no change is forecast and stratus persists for at least one hour.

See5 provides several types of information with its classifier output that are useful in describing classifier performance and structure. Whether using a DT or a RS classifier, each classification model has an associated "confusion" matrix that provides a distribution of how classes of cases (i.e. burn-off or stratus cases) were properly classified (e.g. a burn-off case forecast as a burn-off case) or misclassified (e.g. a burn-off case misforecast as a stratus case). An error rate is provided with the matrix indicating the percentage of all cases evaluated by the classification model that were misclassified. See5 analysis output also provides the number of leaves for a DT or the number of rules for a RS, which is an indication of the complexity of the classifier. In Figure 4, the complexity or size of the DT is 13, since the DT is comprised of 13 leaves. In Figure 5, the complexity or size of the RS is 8, since the RS is comprised of 8 rules. The smaller the numbers, the simpler (fewer number of decisions required to classify a case) the classifier. Table 1 presents the results of this analysis in a matrix form modified from the See5 confusion matrix, to make the results more relevant to the stratus problem. For each

Table 1. Stratus burn-off forecast error distribution matrices per See5 analysis type.

Note: The sum of each matrix column is 100% or 103 cases.

a) Key to the forecast error distribution matrix.

Forecast Method (See5 analysis type)

	Total apparent/true forecast error:	Average % of missed (false) forecasts
burn-off forecast	false-positive	true-positive
stratus forecast	true-negative	false-negative
	stratus observed (103 cases)	burn-off observed (103 cases)

b) Forecast error distribution matrices for each See5 classification analysis.

Decision Tree

	Total apparent forecast error:	7%
burn-off forecast	3.9% (4 of 103 stratus cases)	89.3% (92 of 103 burn-off cases)
stratus forecast	96.1% (99 of 103 stratus cases)	10.7% (11 of 103 burn-off cases)
	stratus observed	burn-off observed

Decision Tree with 10x cross-validation

	Total true forecast error:	25%
burn-off forecast	29.1% (30 of 103 stratus cases)	79.6% (82 of 103 burn-off cases)
stratus forecast	70.9% (73 of 103 stratus cases)	20.4% (21 of 103 burn-off cases)
	stratus observed	burn-off observed

Rule Set

	Total apparent forecast error:	11%
burn-off forecast	12.6% (13 of 103 stratus cases)	91.3% (94 of 103 burn-off cases)
stratus forecast	87.4% (90 of 103 stratus cases)	8.7% (9 of 103 burn-off cases)
	stratus observed	burn-off observed

Rule Set with 10x cross-validation

	Total true forecast error:	28%
burn-off forecast	34% (35 of 103 stratus cases)	77.7% (80 of 103 burn-off cases)
stratus forecast	66% (68 of 103 stratus cases)	22.3% (23 of 103 burn-off cases)
	stratus observed	burn-off observed

analysis method, the error (true or apparent) and distribution of properly forecast (true-positive and negative) and misforecast (false-positive and negative) cases are given in Table 1. Table 2 provides a matrix similar to those in Figure 1 but it defines the tendency (or bias) of the algorithm to forecast a particular condition (i.e. does the algorithm favor forecasting clear or stratus conditions?) and the effect of such a bias (i.e. does the bias favor a forecast that verifies or misses?).

The data archived by the MSI are extensive and comprehensive, but were not designed for this specific analysis (data frequency and regularity are inconsistent). Also, stratus clearing conditions are timed relative to runway operations, not a measured meteorological condition (e.g. LCL higher than the inversion base). These factors may contribute uncertainty to the threshold values specified for the attributes of the classifier (see Figure 6).

The analysis of the stratus problem with See5 entails preparation of a suitable data set. Initially, classes relevant to stratus burn-off will be specified for classification. Next cases will be specified from the MSI database, then attributes will be specified from the MSI database for the given cases, and finally the data set will be analyzed using See5.

4. CLASSIFICATION CONDITIONS

Since the See5 machine learning system assigns case membership to specific classifications, classes must be established that are clearly distinguishable from each other (unambiguous) and representative of the stratus burn-off process. A one-hour time increment will be used to separate classification conditions. The classification conditions are defined relative to the time that the stratus clears over the Bay Area. The MSI has

Table 2. Stratus burn-off forecast bias.

Results are for the Decision Tree with 10-times cross-validation.
Note: Each row sums to 100% of the stratus or burn-off forecasts.

	stratus observed (103 cases)	burn-off observed (103 cases)
burn-off forecast (54.4%, 112 of 206 forecasts)	26.8% missed (30 of 112 forecasts)	73.2% verified (82 of 112 forecasts)
stratus forecast (45.6%, 94 of 206 forecasts)	77.7% verified (73 of 94 forecasts)	22.3% missed (21 of 94 forecasts)

identified 103 stratus burn-off episodes, 47 in 1996 and 56 in 1997 (Appendix A). The MSI, at the time of this writing had not designated episodes for the 1998 season. The basis for designation of a stratus burn-off episode is when SFO landing runways go from single runway (due to visibility obscuration) to dual runway operation. This time is designated as the "@45" time on SFO airport operations logs. One potential drawback is that this threshold is keyed to airport operations whereas the actual meteorological condition when the LCL is equal to the inversion height is not available. It is likely that there is a lag in the time between actual stratus burn-off and initiation of dual runway operations, so such a reference condition is likely to be conservative (the actual time to stratus clearing may be less than one hour). An alternative to SF0 operations as a reference for stratus burn-off times could have been to use SODAR sounding data (for inversion base height) and SFO or SQL ceiling/cloud base data, to see when the ceiling is at the inversion base (clearing). The time when stratus clears over the Bay Area will be referred to as clear. The clear time can be a difficult threshold to specify since stratus burn-off occurs on a horizontal scale in addition to the vertical scale.

Two conditions were designated for classification, one hour prior to stratus clearing and two hours prior to stratus clearing. The first classification condition, one hour prior to clearing, will be referred to as burn-off or BO since the burn-off of the stratus ceiling is in progress over the Bay Area (SFO approach zone specifically). Forecasting the BO condition is the objective of the See5 classification model. The second classification condition will be referred to as stratus or STR. This condition is two hours prior to stratus clearing, and provides the basis for the persistence forecast condition. These conditions were used to isolate attribute values in building the data set from the MSI database for the given cases. The number of cases evaluated are 206 (103 episodes x 2 conditions).

5. DATA

5.1. MSI Data Base

The database analyzed by See5 was derived from the archive of data for the San Francisco Bay Area by the Marine Stratus Initiative. Data available in the archive included: surface observations, incident solar radiation, Oakland upper air soundings, and San Francisco International Airport arrival capacity change times.

Sources for the surface observations were (see Table 3 for a key to station identifiers):

- SAO (hourly data), with station data at CCR, HWD, LVK, NGZ, NUQ, OAK, PAO, RHV, SAC, SJC, SMF, and SQL.
- Automated surface observing system, ASOS, with data acquired every 5 minutes at SFO.
- Automated weather observing system, AWOS, with data acquired every 5 minutes at SMW.
- Pacific Gas & Electric, PG&E, (data every 15 minutes) at ALV, FUN, SMB, SMO, TAM, and UCY.
- MIT Lincoln Labs, MIT/LL, with data acquired every 5 minutes at SFO and SQL.

AFOS files provided a daily summary by the National Weather Service of hourly reports from a variety of meteorological data sources for California, including surface observations, buoy data and model output.

Radiometer data for SFO and SQL were measurements of the downward component of short wave solar radiation at the surface at each station. These data represent surface heating, key to the energy budget of the MBL and to the stratus burn-off process.

Table 3. 3-letter surface station identifiers.

Station	Description (Latitude (°N)/Longitude (°W)/Elevation (m))
alv	Alviso (37.44/121.95/10)
ccr	Concord, Buchanan Field (37.99/122.05/7)
fun	Fort Funston (37.72/122.5/57)
hwd	Hayward Air Terminal (37.66/122.12/14)
lvk	Livermore Municipal Airport (37.69/121.81/121)
nuq	Moffett Field (37.41/122.05/10)
ngz	Alameda NAS (37.78/122.32/4)
oak	Metropolitan Oakland International Airport (37.70/122.22/1)
pao	Palo Alto Airport (37.47/122.12/2)
rhv	San Jose Reid/Hillview (37.33/121.82/41)
sac	Sacramento Executive Airport (38.51/121.50/6)
sfm	SFO MIT/LL [sfo_ll] (37.62/122.36/3)
sfo	San Francisco International Airport ASOS (37.62/122.36/3)
sjc	San Jose International Airport (37.36/121.92/17)
smb	San Mateo Bridge (37.56/122.23/1)
smf	Sacramento Metropolitan Airport (38.70/121.59/7)
smo	San Mateo (37.51/122.25/2)
smw	San Mateo (37.56/122.23/2)
sql	San Carlos Airport AWOS (37.52/122.25/1)
sqm	San Carlos MIT/LL [sql_ll] (37.52/122.25/1)
tam	Mt. Tamalpais (37.92/122.6/762)
ucy	Union City (37.60/122.1/2)

SODAR data for SFO and SQL were measured using monostatic acoustic sounders to provide an indication of inversion base. The SODAR signal is a representation of atmospheric refractivity, with a discontinuity expected at the MBL/subsidence inversion boundary.

5.2. Data Selection and Preparation

A significant portion of the work in preparing the See5 analysis was the extraction and preparation of the analysis data set from the MSI archive (~0.87 gigabytes of data). The baseline data set used for evaluation by See5, after extracting only the desired attributes for the desired conditions for the specified cases to be classified, was a tabular ASCII file (~123 kilobyte data file) (Appendix B). Due to missing data and data mismatches with condition times, some adjustment was necessary to match available measured data to the condition times in the analysis database.

Although the MSI archive provided ample surface station data for evaluation by See5, some criteria had to be established to keep the data set at a manageable size and to remove redundant or low quality data. The selection criteria were: data acquisition frequency, the reliability of the data acquired, whether a station's data were redundant or inferior to a proximate station, the number of attributes measured at a station, and the location of the station within or proximate to the San Francisco Bay.

Data acquisition frequency was vital since condition times did not necessarily coincide with the time data were acquired. For data acquired hourly, it was not unusual for data to be acquired at a time up to a half-hour prior to or following the desired condition time. When faced with the choice of selecting data up to a half-hour earlier or later than the condition time, the decision was to defer to the earlier data. Since conditions develop from stratus through burn-off to clearing, selecting an earlier point would be a conservative choice, preventing premature forecasting of the burn-off condition. In spite of their low frequency, some stations acquiring data hourly were used since no suitable alternates were available proximate to these stations. Stations with data acquired every 15 minutes (PG&E) were acceptable and stations with data acquired every 5 minutes (AWOS, ASOS, and MIT/LL) were ideal. With more frequent data acquisition, if a data point was missed or a variable within a data point was missed, a point earlier or later could be substituted that was likely to still be representative of the condition, otherwise the data would have to designated as missing (using "?" in the data set).

The reliability of the data acquisition for some stations was a key selection point. If a station had data missing for a large percentage of the case days, these stations would not contribute enough data to formulate a pattern in the process. Since only 103 case days were available, significant gaps in the data for a given attribute would only cause fragmentation of the pattern in the results.

The proximity of a station to other stations, which is the case particularly for SFO and SQL, required that some stations be culled. This reduced the volume of inputs to See5 for analysis and avoided overfitting of the results. Some stations had fewer measurements than other stations, therefore limiting the use of derivative attributes, such as gradients or rates, between stations. Data from stations outside of the Bay Area were ignored to keep the size of the database manageable. The justification used in ignoring this data was that these surface stations may have limited correlation to the stratus burn-off over the Bay Area due to the short (1-2 hour) time scales considered for this analysis. Those stations along the coast (except Fort Funston), offshore (buoys) and in the San Joaquin Valley were excluded.

The decision of which station's data to use was subjective and was based upon the criteria stated earlier. Not including data available from the AFOS summary, there were data available for 22 surface stations. Of these, 11 were excluded for the following reasons: Alviso (alv) is close to Moffett Field (nuq), and its data had low quality, reliability and frequency. Alameda NAS (ngz) had too much missing data and the station was projected to close. Sacramento (sac and sfm) had low frequency data and was outside of the Bay Area. SFO MIT/LL (sfo_ll) was redundant with SFO and had too much missing data (initially 16 of 103 cases). San Mateo Bridge (smb) was unreliable, missing data for 71 cases. San Mateo (smo) had lower frequency data (every 15 minutes) versus nearby smw (every 5 minutes). San Carlos Airport (sql) had lower frequency (hourly) data than nearby MIT/LL San Carlos (sql_ll) (every 5 minutes). Union City (ucy) had very unreliable, low frequency data. Livermore (lvk) and Concord (ccr) were excluded since they were outside of the Bay Area. Figure 1 shows the locations of the surface stations used and their location relative to SFO and the SFO approach path.

Some limitations were notable in extracting surface observation data from stations. Some stations were not recording data prior to burn-off times due to limited monitoring hours, which appeared to be keyed to periods of daylight. These gaps in data often occurred during the conditions being evaluated, degrading the data available to forecast them. For some stations there were data gaps due to frequent lost connections to the archiving computer or due to unreliable data acquisition. Often data were not captured for 1 of the 2 conditions (BO or STR) at a given station on any given case day. Such a pattern of missing data potentially reduces the ability to recognize patterns that would be evident in continuous data.

6. ATTRIBUTES

Attribute selection was dictated by the types of data that were available for the stratus episodes from the MSI database. The majority of the data is used in raw form as it was measured. Attributes or variables are chosen based upon their relevance to the fog/stratus process (e.g. LCL and inversion height). The measurements available from the MSI are primarily surface based (e.g. surface temperature, dewpoint temperature, wind speed and direction), which are somewhat relevant to the stratus burn-off process, but are less so than measurements of the stratus cloud condition (i.e. LCL, inversion base height, etc.).

6.1. Measured (Raw) Attributes

Many of the attributes to be discussed were measured at more than one station. In such cases, the attribute name, as referenced, will contain xxx, which represents the 3-letter surface station identifier (Table 3). The names, descriptions and units of all variables utilized in this analysis are summarized in Table 4. For a ML analysis it is crucial that the variables used have utilized a consistent measurement. If an instrument has gone out of calibration during the acquisition of the training data, drift may occur in the data that will increase uncertainty in the results.

Table 4. Attribute names and descriptions.

Note: xxx represents the 3-letter station identifier identified in Table 3.

Attribute	Description (units)
JulDate	Elapsed number of days to the case date from the beginning of the year of the case.
TimeZ	Greenwich Mean Time (hr) of case condition.
VVVeta	Vertical velocity (mb/hr) from 12Z + 6hr Eta Model output.
LIeta	Lifted Index (°C) from 12Z + 6hr Eta Model output.
VVVngm	Vertical velocity (mb/hr) from 12Z + 6hr NGM Model output.
LIngm	Lifted Index (°C) from 12Z + 6hr NGM Model output.
xxxInHt	Inversion height (ft) computed from SODAR data.
xxxInSt	Inversion strength (non-dimensional) computed from SODAR data.
xxxCld%	Cloud fraction (%) from AWOS.
xxxCldBs	Cloud base height (ft) from AWOS.
SolAng	Solar altitude angle (deg.) computed using Sun Position shareware from Seattle Energy Works.
xxxRad	Incident SW solar radiation (watts/m^2).
xxxT	Surface temperature (°C).
xxxRH	Surface relative humidity (%).
xxxP	Surface barometric pressure (mb).
xxxTd	Surface dewpoint temperature (°C).
xxxWdd	Surface wind direction (deg.).
xxxWdr	Surface wind direction converted to an 8-point rose (N, NE, E, SE, S, SW, W, NW).
xxxWs	Surface wind speed (m/s).
xxxTA	Surface thermal advection (°C·m/s) between SFO and station xxx.
xxxdT	Differential temperature (°C) between the temperature at condition time and the minimum temperature for the case date at the station.
xxxdt	Time differential (hr) between the condition time and time of the minimum temperature for the case date at the station.
xxxdP	Pressure differential (mb) between SFO and station xxx.

The following are the descriptions and variable names for each of the raw attributes considered. The Greenwich Mean Time for the case condition (TimeZ) may relate patterns in the diurnal stratus cycle to stratus burn-off. (The episodes occurred during daylight savings time so Z time is 7 hours ahead of Pacific Daylight Time [PDT]). The cloud fraction (xxxCld%) may relate cloud cover to the burn-off process. The cloud base height (xxxCldBs) may relate the LCL to burn-off. The short wave, solar insolation measured by a radiometer (xxxRad) may relate MBL heating to burn-off. The surface temperature (xxxT) may also relate MBL heating to burn-off. The surface barometric pressure (xxxP) may relate variations in the pressure field over the Bay Area to burn-off. The surface dewpoint temperature (xxxTd) may relate the MBL condensed moisture capacity and the LCL to burn-off. The surface wind direction, in degrees, (xxxWdd) may relate advection to burn-off. The surface wind speed (xxxWs) may provide a threshold value if advection correlates to burn-off. The vertical velocity from the 12Z Eta and NGM models (VVVeta and VVVngm, respectively), at 12Z + 6 hours for SFO, may relate the subsiding or rising air associated with larger scale synoptic conditions to burn-off. The lifted indices from the 12Z Eta and NGM models (LIeta and LIngm, respectively), at 12Z + 6 hours for SFO, like vertical velocities, may also relate subsiding or rising air associated with larger scale synoptic conditions, or inversion strength with burn-off.

6.2. Derived Attributes

In machine learning a derived attribute may be more relevant to a pattern for a particular condition than the individual attributes that make it up. This is because machine learning only defines linear thresholds, perpendicular to an attribute axis in a description space (Figure 6). If an attribute that defines the process being classified is derived from a nonlinear combination of other attributes (i.e. relative humidity is a function of temperature, dewpoint temperature and pressure), the threshold for the derived attribute may better classify cases than linear combinations of individual attributes, and may reduce the complexity of the classifier (use less decisions to define a condition). Attributes that may appear noisy on their own, may be highly predictive when combined with other attributes (Weiss & Kulikowski 1990). An example of a derived variable that is non-dimensional, but is very representative of a physical process is the Richardson Number, a measure of boundary layer stability. One potential drawback with this data set is the consideration of gradients between stations when stations do not acquire data at the same frequency. Horizontal spatial gradients using data not taken at the same time or at unequal frequencies may introduce a spurious time derivative to the gradient.

The following are the variable names and descriptions for each of the derived attributes considered. JulDate, is derived as the elapsed number of days to the case date from the beginning of the year of the case. It provides a means of correlating time of year to cases from more than one year and provides a continuous variable relevant to seasonal variation or climatology. This attribute may be more useful with more than 2 years of stratus episodes to train with, since more cases would be available to support selection of a threshold at a given Julian Date.

xxxInHt and xxxInSt, are the inversion height and strength computed using a simple algorithm (SA) which uses SODAR data as input. The SA algorithm was designed to objectively compute the inversion height and strength using the statistical average and the maximum value of the sounding data for each sounding. Sounder data were acquired approximately every minute. The data were comprised of 80 values, each representing atmospheric refraction at 25 foot increments in height from the surface, where the acoustic sounder was located. Readings were taken from approximately sea level to 4000 feet of altitude. Determination of the inversion height was based upon the maximum signal (and its corresponding height from the surface) of the signals from 175 feet to 4000 feet. The first 6 sounding signals (surface to 150 feet of altitude) were ignored due to exaggerated signal values, possibly due to surface noise pollution (adjacent U.S. Highway 101 and aircraft operations), reverberation from surface structures, or reflection from surface based inversions. All of the signals (from 175 ft to 4000 ft) were then normalized by the mean. All values that were less than one standard deviation from the mean were set to a zero value. This operation was based upon the assumption that these values are below the background average, with the target inversion values being greater than the background average value. The maximum value was then found from the set of values, which was used to define the inversion height. From this approach the inversion strength was also defined. It is the ratio of the maximum signal at the inversion to that of the background average. This algorithm only required the SODAR data, which were in fact one of the more reliably acquired attributes. This in turn allowed the algorithm to provide inversion height and strength attribute data for most of the cases. Although, the

SA algorithm is not rigorous, it may demonstrate a pattern, at least qualitatively representative of the inversion. This type of attribute is well suited to machine learning, which attempts to recognize patterns in the data.

Inversion height and strength determine the top of the stratus cloud, and relative to the LCL determines the thickness of the stratus deck, and the potential for entrainment through the top of the stratus. These attributes may also detect the passage of gravity waves or synoptic short waves, manifested as short-period (on the order of an hour) oscillations in the inversion height attribute value.

MIT/LL generated inversion heights and strengths at SFO and SQL using a complex method, with thorough validation (SFO ASOS ceiling as truth), such that their results matched the observed heights. Unfortunately, with the MIT/LL method, if all of the inputs required for the algorithm are not available, an inversion height and strength can not be computed. Because of frequent gaps in the data set, only a minority of case dates (~10% of the MSI stratus episodes) had inversion data defined by the MIT/LL algorithm. The SA algorithm was utilized as an alternative to the MIT/LL method to provide data for analysis in more cases. Although the MIT/LL values may be more accurate for the inversion's height and strength, the lack of data limits the ability of See5 to correlate the attribute with a pattern in the process. The MIT/LL attributes were included in the initial data set for initial trials with the See5 analysis. During these trials, if an inversion attribute was selected, it was a SA inversion attribute. Since the SA and MIT/LL attributes are similar (functions of the SODAR data) the availability of two similar attributes would potentially fragment a pattern in the process relevant to the SODAR data. To prevent such fragmentation, the SA data was kept and the MIT/LL data was removed based upon the prevalence of the SA attributes and the results of the trial analyses. The SA method, although physically less rigorous, provides qualitative data for almost all cases.

SolAng, is the solar altitude angle (β) (see Appendix D for the equation for β) computed using Sun Position (1998) software, which may relate incident SW radiation and time of year to MBL heating and subsequent stratus burn-off.

xxxRH, is the computed surface relative humidity (see Appendix D for the equation for RH), which provides a measure of atmospheric moisture levels relative to saturation. RH was computed at stations that measured T, Td and P. Those stations without all 3 variables could not compute RH. If Td was available for a station, then it was used if RH was not computable. RH as a combined attribute may possibly reveal more patterns than Td by itself. The differential between ambient and dewpoint temperature could have also been considered as an attribute, but was not for this analysis. RH was chosen since it incorporates barometric pressure into the attribute and since it provides values on an absolute scale (0 to 100%).

xxxWdr, is the surface wind direction converted to an 8-point wind rose. A 16-point wind rose was initially considered, but the 8-point wind rose performed better. When the 16-point rose was tested with the data, it was found to overfit the classification by fragmenting the data cases, therefore having too few cases to support each discrete rose point. Conversion of the wind direction data to an 8-point (or 16-point) wind rose was potentially useful for two reasons. First it avoided the 0 and 360 degree discontinuity and second, it allowed for the classification of wind direction as a discrete variable. It should be noted that the precision of wind direction data varied significantly between stations: some stations reported wind direction in 1° increments, and others in 10° increments.

xxxTA, is the surface thermal advection between SFO and station xxx. Thermal advection was computed between selected stations that possessed suitable temperature and wind data. This attribute may relate patterns in the sea breeze circulation, coastal advection fog and local drainage flows to stratus burn-off. Thermal advection is defined as,

$$\text{xxxTA} = -\mathbf{V}\text{xxx} \bullet \nabla\text{Txxx}. \qquad (2)$$

The following method is used for computing this value. First a unit vector is defined between SFO and the subject surface station. This is done by determining the bearing from station xxx toward SFO using the latitude and longitude coordinates of each location. The coordinates for the 6 stations used in computing TA are (Lat (d.dd) / Lon (d.dd):

SFO	-	37.62° / 122.36°
fun	-	37.72° / 122.50°
hwd	-	37.66° / 122.12°
nuq	-	37.41° / 122.05°
sql	-	37.52° / 122.25°
tam	-	37.92° / 122.60°

From these coordinates a unit vector is computed between SFO (positive toward SFO) and the subject station xxx using,

$$\mathbf{u}\text{xxx} = [\Delta\text{Lat}\,\mathbf{i} + \Delta\text{Lon}\,\mathbf{j}] / [\Delta\text{Lat}^2 + \Delta\text{Lon}^2]^{0.5} \qquad (3)$$

$$\Delta\text{Lat} = \text{LatSFO} - \text{Latxxx}$$

$$\Delta\text{Lon} = \text{LonSFO} - \text{Lonxxx}.$$

From this conversion, the corresponding station unit vectors and compass heading in degrees between SFO and stations xxx are:

ufun	=	+0.814**i** - 0.581**j**	(125.52°)
uhwd	=	-0.986**i** - 0.164**j**	(260.56°)
unuq	=	-0.828**i** + 0.561**j**	(304.12°)
usql	=	-0.740**i** + 0.672**j**	(312.24°)
utam	=	+0.625**i** - 0.781**j**	(141.33°)

The temperature differential between the stations, Tsfo - Txxx, was then multiplied by the unit vector to define the temperature gradient, ∇T, between SFO and the stations,

$$\nabla Txxx = \mathbf{uxxx} * (Tsfo - Txxx). \tag{4}$$

Next, the wind direction and speed at SFO and the stations were converted into u and v vector components. The vectors were then subtracted to define the advection, **V**xxx, in vector form, between SFO and the stations. Having ∇Txxx and **V**xxx, the dot product of -**V** and ∇T were taken, yielding the thermal advection between SFO and the subject station. A positive value indicates warm air advection toward SFO.

xxxdT, is the differential temperature between the temperature at condition time and minimum temperature for a given case date. This attribute may relate temperature threshold values for MBL heating sufficient for stratus burn-off. xxxdt, is the time difference between the condition time and the time of the minimum temperature with units of hh.mm. This attribute may relate temporal patterns in MBL heating relevant to stratus burn-off. For each case date, the minimum temperature and corresponding time were determined by inspection. Since stratus burn-off is dependent upon heating of the MBL, the differential in time and temperature from this minimum condition may provide reference points for the MBL heating process. These attributes were selected because of the pattern observed during data extraction that indicated that fog/stratus is "thickest" (ceiling lowest, T ~ Td, RH maximum) at local minimum temperature, thus posing a potentially significant classification attribute.

xxxdP, is pressure gradient between SFO and station xxx, which may relate to variations in the larger scale pressure field. Positive values are for a positive pressure gradient toward SFO.

The combination of the aforementioned attributes and surface stations provide a total of 92 measured and derived attributes for analysis by See5. A baseline data set (Appendix B) of 92 attributes for 2 conditions (STR and BO) for 103 stratus burn-off episodes (creating 206 cases) was derived from the MSI database.

7. RESULTS

The data set was evaluated using several See5 processing options. The See5 analysis constructed classification models in the form of a decision tree and a rule set. Additionally, the data set decision tree and rule set classifications were evaluated for their true error rate using 10-times cross-validation. 10-times cross-validation was used due to the limited size of the training data set (103 stratus episodes).

7.1. Forecast Accuracy and Skill

The forecast matrices in Table 1 are derived from the original See5 analysis confusion matrices and provide a comparison of the analysis results for the DT and RS classification models of the stratus problem and their corresponding cross-validation results. The error given for each analysis is the percentage of all cases that were misforecast by the classification model. The terms on the major diagonal of the matrix (lower left and upper right corners) represent the percentage of correct forecasts of persistence or change (true-negative or true-positive, respectively) for the given outcome (stratus or burn-off). The terms on the other diagonal (upper left and lower right corners) represent the percentage of misforecasts of change or persistence (false-positive or false-negative, respectively). The columns of the matrix represent observation or verified conditions (stratus or burn-off), whereas the rows of the matrix represent the forecast conditions (stratus or burn-off). The left matrix columns represent the results of forecasting 103 stratus cases and the right columns represent the results of forecasting 103 burn-off cases from the training data set. The sum of the percentages of each column is 100%. These matrix results provide the best indication of the classification model performance in forecasting stratus burn-off.

The results in Table 1 indicate for the forecast decision tree with ten-times cross-validation in Figure 4, that stratus burn-off (a true-positive) will be properly forecast in 80% of the burn-off events, and that stratus persistence (a true-negative) will be properly forecast in 71% of the persistence events. For 29% of the persistence events when burn-off is forecast stratus persists (a false-positive), and for 20% of the burn-off events when stratus persistence is forecast burn-off occurs (a false-negative). The tendency of the DT is to forecast a false-positive, which is an optimistic forecast, with a tendency towards forecasting burn-off. A false-negative forecast would be preferable to a false-positive forecast since its consequence, relative to SFO operations, is that airport capacity will be under-committed versus over-committed for a false-positive forecast.

The bias of the forecast decision tree (with ten-times cross-validation) against actual occurrences (206 observed cases in the training data set) is evaluated in Table 2. Table 2 provides a matrix similar to Table 1, but with the emphasis on the tendency of the decision tree to make either a stratus or burn-off forecast. The table demonstrates the accuracy of the forecasts of the decision tree considering its tendency to make a particular forecast (either stratus or burn-off). In Table 2, the sum of the percentage of each row is 100% (versus 100% for each column in Table 1). From Table 2, the decision tree forecasted stratus burn-off 112 times or 54% of the time and forecasted stratus persistence 94 times or 46% of the time. For burn-off forecasts, 82 of the 112 (73%) forecasts verified, versus 30 of the 112 (27%) forecasts missed. For stratus persistence forecasts, 73 of the 94 (78%) forecasts verified, versus 21 of the 94 (22%) forecasts missed. In summary, considering the performance of the forecast decision tree, there is a 73% chance that the decision tree forecast of burn-off within an hour will verify, and a 27% chance that a burn-off forecast within an hour will not verify. If stratus persistence is forecast, there is a 78% chance that it will verify and a 22% chance that it will not verify (burn-off will occur within an hour). This representation of the results indicates that the bias towards forecasting burn-off (54% of forecasts versus 50% without bias) yields an optimistic forecast in favor of burn-off, with a 27% chance that when burn-off is forecast to occur within an hour, stratus will persist.

7.2. Decision Tree versus Rule Set Performance

The results of the See5 analysis on training data alone (without cross-validation) indicate that the DT fits the training data better than the RS (7% versus 11% apparent error). Analysis of the training data with cross-validation indicated that the average error (of 10-times validation), an approximation of the true error rate of the classification model, was 25% for the DT versus 28% for the RS. This is contrary to the expectation that the RS true error rate would be better than that of the DT since the generalized RS should better predict unseen cases. This result may have been due to the DT fitting a majority of the burn-off training cases (68%) via the path described by bold arrows in Figure 4. Cases that do not match this path are spread to a number of leaves throughout the DT. Since the RS may prune these leaves, the ability to fit the non-majority cases may be diminished. As a forecast tool, the DT classification model would be preferred for the stratus problem.

7.3. Attributes Chosen

In Appendix C the attributes available and applied to each classification scheme are identified. From this table 10 of the 92 available attributes were applied by the See5 analyses to the stratus burn-off process in building the DT and RS classification models.

NuqdT and fundT, are the differences between the temperature at the condition time and the minimum temperature for the case date at Moffett Field and Fort Funston, respectively. Selection of these attributes indicates the importance of MBL heating to the burn-off process. Moffett Field is located at the southern extent of the San Francisco Bay at the boundary between the bay and valley. Fort Funston (on the coast side of the San Bruno Gap) is at the northern extent of the San Francisco Bay at the boundary between the coast and bay.

NuqRH and smwRH, are the relative humidities at Moffett Field and San Mateo, respectively. Selection of these attributes indicates the role of MBL moisture content, specifically at the middle and southern extent of the San Francisco Bay, in the stratus burn-off process. These attributes may be relevant to the burn-off process since stratus may dissipate towards the mouth of the bay from the South.

SfoInHt, sqlInSt, and sfoCldBs, are the inversion height at SFO, the inversion strength at San Carlos, and the cloud base height over SFO, respectively. The fact that stratus burn-off occurs when the LCL rises above the inversion base height explains the inclusion of these variables.

JulDat, TimeZ, are the Julian date of the stratus episode and GMT time of the condition. Selection of these attributes indicate that stratus burn-off may vary temporally on seasonal and diurnal scales.

Sfodt, is the differential from the condition time to the time of the minimum temperature for the case date at SFO. It is interesting that time differential was used here rather than the temperature differential that was used at nuq and fun. This attribute indicates that the rate of surface heating versus the amount of surface heating at SFO is important to the burn-off process.

The distribution around the Bay Area of attributes applied by the See5 analysis of the stratus burn-off data set, is illustrated in Figure 7. This figure indicates a propensity for attributes that correlate to stratus burn-off to lie on the western edge of the San Francisco Bay, proximate to the SFO approach path, perhaps an indication of the role of the Bay in the stratus process.

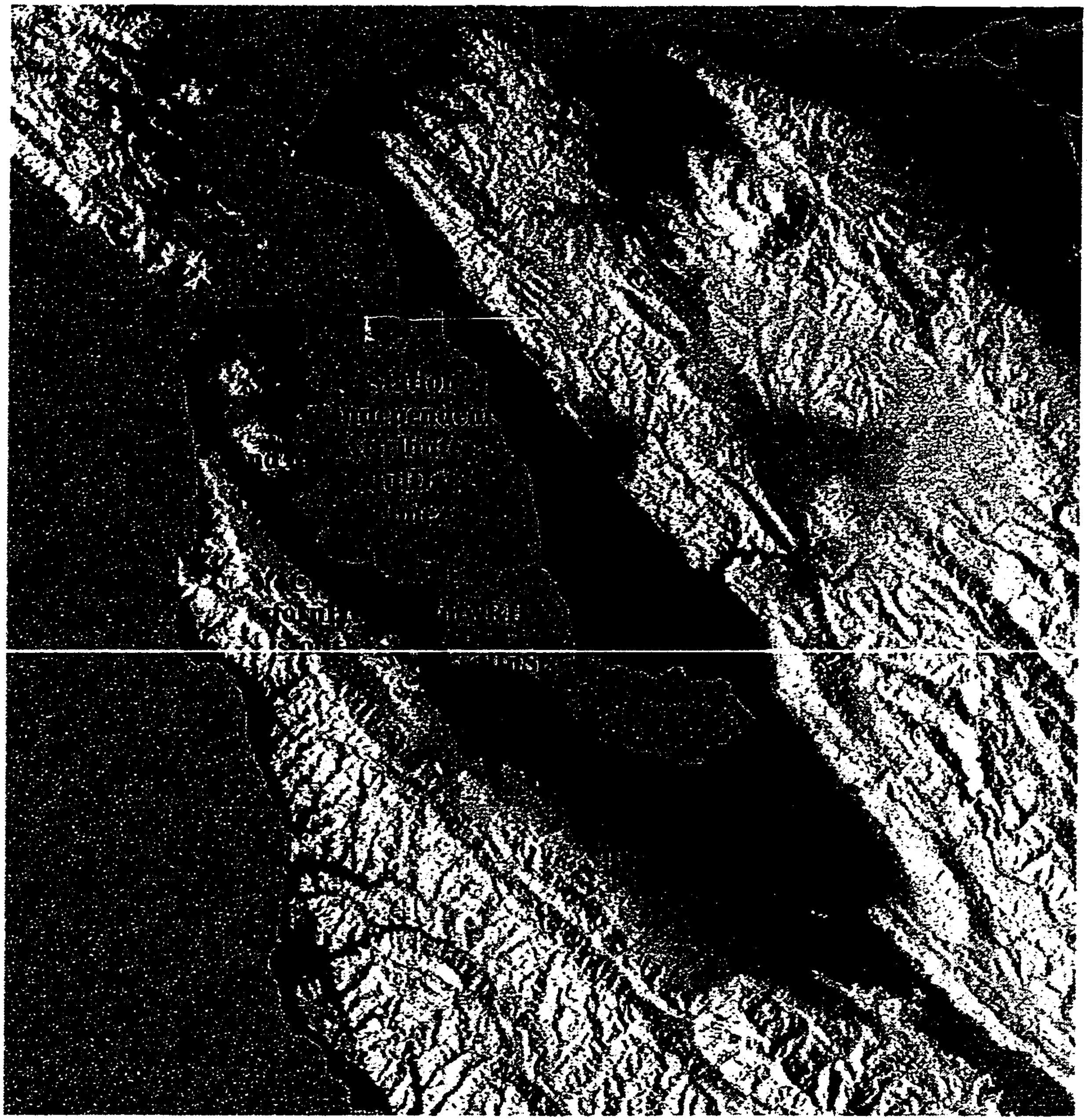


Figure 7. Ten attributes utilized by the See5 analysis to forecast stratus burn-off over the San Francisco Bay Area.

The threshold values of the attributes applied by the decision tree classification model can be found in Figure 4. The threshold values for the attributes that differentiate a forecast of the burn-off condition from the stratus condition are:

nuqdT	>	1°C
sfoCldBs	>	822 feet
sqlInSt	>	7 (inversion sounding is 7 times the background average)
fundT	>	0.9°C.

From Figure 4, the threshold values of attributes for intermediate (non-terminal, applicable to both the stratus and burn-off conditions) decisions within the decision tree are:

smwRH	> or ≤	62%
JulDat	> or ≤	206^{th} day of the year
TimeZ	> or ≤	14.95Z
sfodt	> or ≤	0.5 hour
nuqRH	> or ≤	83%
sfoInHt	> or ≤	425 feet.

As the root attribute, smwRH is important because all cases being forecast are subject to a decision based upon this attribute.

It is interesting to note that advection attributes, i.e. direction, wind speed and thermal advection, represent 43% of all available attributes (40 of 92). In spite of this preponderance, none of these advective attributes evidenced a pattern in the data applicable to forecasting stratus burn-off. These results may indicate that the stratus burn-off process is (at least for the 2 hours preceding stratus clearing) primarily a balance of a heat and moisture budget in the Bay Area as proposed by Clark and Wilson (1996). Perhaps if more training cases were available patterns would be evidenced that relate advection to the burn-off process. Currently, the limited data set may best support a generalized heat and moisture budget model for the final two hours of the stratus burn-off process.

7.4. Data Quality

As stated earlier, there is a concern about the quality of the data set, specifically the lack of consistent data available from the MSI database. Upon evaluation of the data set a significant amount (20%) of all attribute data were missing. Some attributes critical to the stratus burn-off process may have been ignored due to under-representation during the classifier analysis. Figure 8 and Appendix C show that there is some correlation between cases that were misforecast and the amount of case data that was missing. Many of the cases (17 of 26) that were misforecast were early in the data set (the first 19 cases out of 103) when there were significant gaps in data, particularly sounding data, which is required for the sqlInSt attribute key to forecasting 68% of the training BO cases. If the first 19 cases were ignored, the apparent classification accuracy would be approximately 95%. A larger database would allow culling of cases with low data quality. Figure 9 illustrates the correlation between attributes that correlated to the stratus burn-off process and the amount of data available for the attribute in the training data set. Nine of the ten attributes applied had data available at or below the average amount (20%) of missing data for the whole database, which indicates the importance of having consistent data to determine a pattern using ML methods.

8. CONCLUSIONS

Artificial intelligence methods may be useful tools for analyzing meteorological processes that are physically complex, but well defined by empirical data. The objective

Figure 8. Training cases misforecast versus data availability.

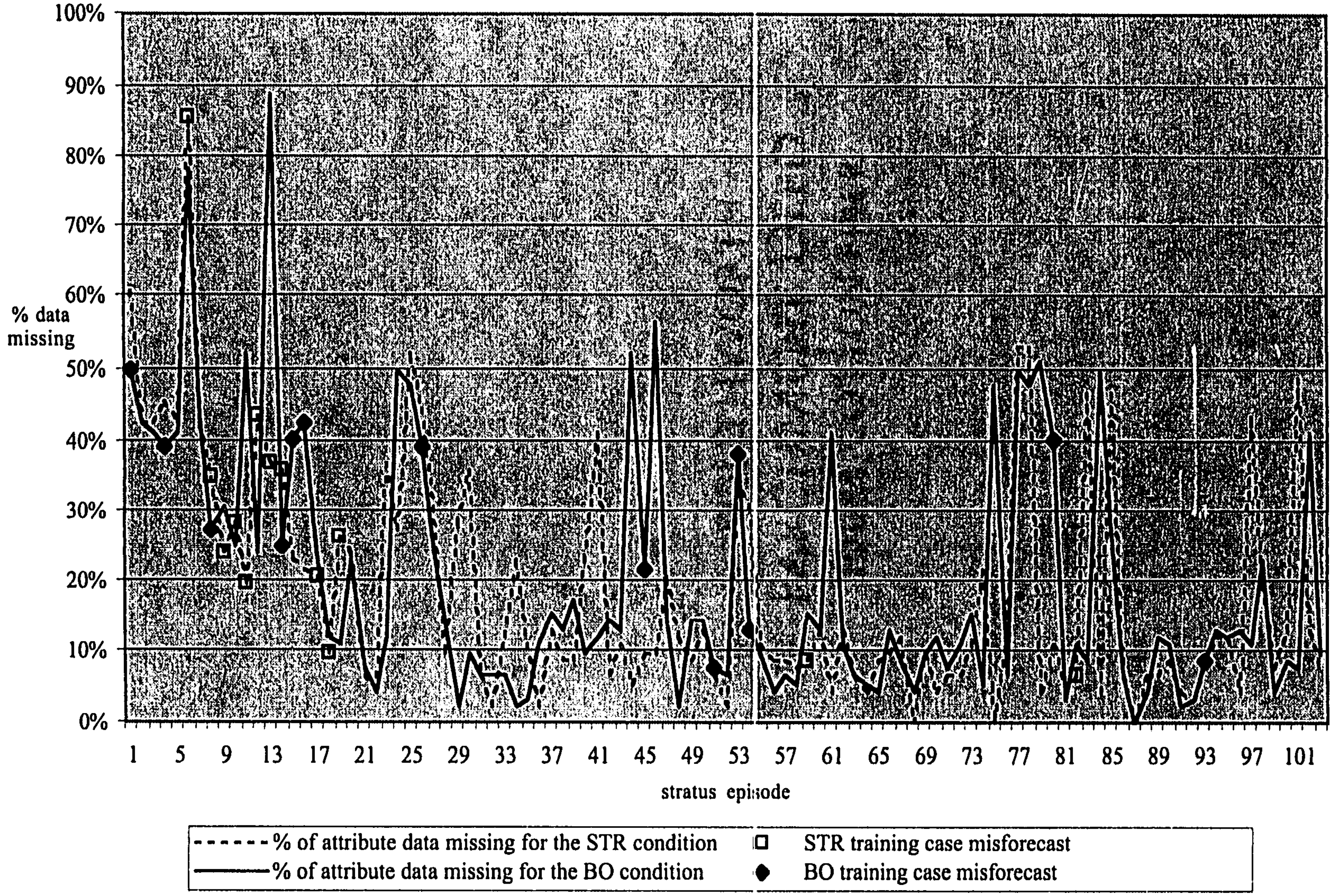
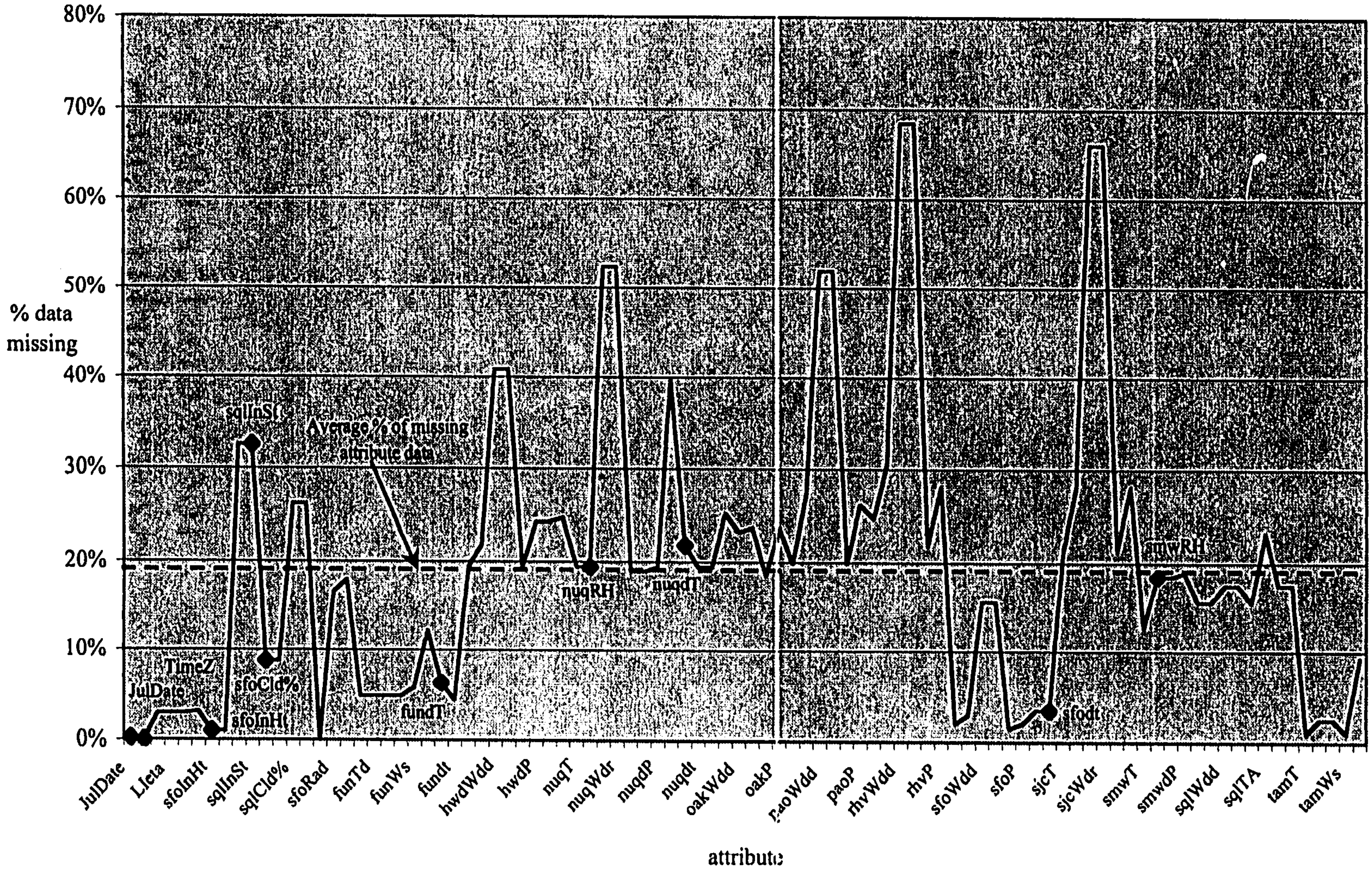


Figure 9. Forecast attribute utilization versus data availability.
Forecast attributes are indicated by diamonds and labels. The plotted line represents the percent of missing data for each attribute.



of this research was to demonstrate the potential of applying machine learning to aid in the forecast stratus burn-off over the San Francisco Bay. The results of this work appear to concur with the conclusions drawn by Tag and Peak (1996), that machine learning has twofold applicability, providing tools for data analysis and prediction, and improving the understanding of relevant physical processes.

Diagnostically, the See5 analysis has provided an objective analysis of the stratus burn-off process with the data that it was provided and for the conditions it was tasked to classify. This form of analysis may be valuable in testing the correlation of new attributes to the burn-off process. Identification of these attributes and consistent threshold values indicate that there are recognizable patterns during stratus burn-off and that the See5 analysis is capable of revealing these patterns. The See5 analyses results concur with the premise of the MSI, that the final stratus burn-off process is defined by an energy budget and moisture phase change in the quasi-closed system of the San Francisco Bay.

The attributes identified support a final stratus burn-off process based upon a balance of thermal heating and moisture phase change within the well-mixed marine boundary layer of the Bay. Advective terms did not evidence a relationship to the burn-off process in the analysis. In spite of this result, there may be an indirect relationship of advective processes with the minimum temperature difference attributes at Moffett Field as a source of warm, dry inland air and at Fort Funston as a source of cool, moist marine air.

The results of the analysis have indicated the importance of data quality, specifically to the machine learning evaluation, and in general to the overall representation of the processes being studied. For the baseline data set a significant amount (20%) of the data were missing. Since machine learning relies upon consistent and representative data to recognize patterns, if data quality improves, so may the ability of machine learning to accurately forecast stratus burn-off.

The machine learning results, in the form of decision trees and rule sets, with attributes and corresponding threshold values identified, are compatible with human reasoning versus other artificial intelligence methods that function as a "black box" (results cannot be related directly to their inputs). From the classification analyses, the classification models (RS and DT) demonstrated the ability to properly identify or forecast cases one-hour prior to stratus clearing in 78 to 80% of its forecast attempts, respectively. The random probability of properly classifying these cases is 1 in 2 or 50%. These results indicate that the classifier has demonstrated some skill in accurately defining conditions one-hour prior to stratus clearing over the Bay. The analysis results in the form of a DT (Figure 4) or a RS (Figure 5) could be easily assimilated as a computer algorithm to provide operational forecast guidance.

This thesis demonstrates the potential of machine learning as an alternative source of real-time forecast guidance for operational applications which may promote further investigation into the application of machine learning to meteorological problems. The field of machine learning is relatively young, and its technology is constantly advancing. Its application with quality data may yield even better solutions to meteorological problems such as forecasting stratus burn-off over the San Francisco Bay.

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Appendix A. Marine Stratus Initiative stratus episodes.
Dates and times are based upon the start of dual runway operations at SFO following the change in aircraft visual range from IFR to VFR conditions.

Date	Julian Date	Greenwich Mean Time	Pacific Dayligtht Time
5/27/96	96148	1448	748
5/29/96	96150	1745	1045
6/15/96	96167	1850	1150
6/20/96	96172	1939	1239
6/21/96	96173	1735	1035
6/24/96	96176	1945	1245
6/25/96	96177	2108	1408
7/4/96	96186	1545	845
7/7/96	96189	1636	936
7/8/96	96190	1735	1035
7/9/96	96191	1710	1010
7/10/96	96192	1820	1120
7/11/96	96193	1645	945
7/13/96	96195	1618	918
7/14/96	96196	1725	1025
7/15/96	96197	1805	1105
7/22/96	96204	1624	924
7/23/96	96205	1655	955
7/24/96	96206	1745	1045
7/25/96	96207	1740	1040
7/26/96	96208	1820	1120
8/7/96	96220	1930	1230
8/8/96	96221	1741	1041
8/15/96	96228	1810	1110
8/17/96	96230	1750	1050
8/20/96	96233	1639	939
8/22/96	96235	1635	935
8/24/96	96237	1832	1132
8/25/96	96238	1834	1134
8/26/96	96239	1920	1220
8/27/96	96240	1615	915
9/2/96	96246	1722	1022
9/3/96	96247	1907	1207
9/11/96	96255	2227	1527
9/13/96	96257	1822	1122
9/15/96	96259	2155	1455
9/23/96	96267	1800	1100
9/24/96	96268	1710	1010
9/25/96	96269	1929	1229
9/26/96	96270	1922	1222
9/27/96	96271	1925	1225
9/28/96	96272	1852	1152
9/29/96	96273	1905	1205
9/30/96	96274	2208	1508
10/1/96	96275	2147	1447
10/2/96	96276	1943	1243
10/3/96	96277	1805	1105
5/10/97	97130	1845	1145
5/11/97	97131	1835	1135
5/12/97	97132	1630	930
5/14/97	97134	1628	928
5/23/97	97143	2050	1350

Date	Julian Date	Greenwich Mean Time	Pacific Daylight Time
5/27/97	97147	1400	700
5/31/97	97151	1436	736
6/8/97	97159	1615	915
6/17/97	97168	1618	918
6/28/97	97179	1938	1238
7/4/97	97185	1800	1100
7/5/97	97186	1820	1120
7/13/97	97194	1653	953
7/14/97	97195	1655	955
7/15/97	97196	1650	950
7/18/97	97199	1619	919
7/19/97	97200	1600	900
7/20/97	97201	1751	1051
7/21/97	97202	1645	945
7/26/97	97207	1713	1013
7/27/97	97208	1657	957
7/28/97	97209	1724	1024
7/29/97	97210	1720	1020
7/30/97	97211	1720	1020
7/31/97	97212	1722	1022
8/6/97	97218	1630	930
8/8/97	97220	1646	946
8/9/97	97221	1645	945
8/11/97	97223	1720	1020
8/12/97	97224	1752	1052
8/13/97	97225	1745	1045
8/14/97	97226	1900	1200
8/15/97	97227	1645	945
8/16/97	97228	1750	1050
8/17/97	97229	1910	1210
8/23/97	97235	1924	1224
8/24/97	97236	1608	908
8/25/97	97237	1648	948
8/26/97	97238	1630	930
8/29/97	97241	1925	1225
8/30/97	97242	1734	1034
9/2/97	97245	1730	1030
9/3/97	97246	1630	930
9/7/97	97250	1742	1042
9/11/97	97254	1752	1052
9/12/97	97255	1555	855
9/13/97	97256	1735	1035
9/15/97	97258	1630	930
9/22/97	97265	1735	1035
9/26/97	97269	1830	930
9/30/97	97273	1730	1030
10/1/97	97274	1835	1135
10/2/97	97275	1745	1045
10/9/97	97282	1645	945
10/21/97	97294	1848	1148
10/22/97	97295	1935	1235

Appendix B. Stratus burn-off training data set.

Year	JulDate	TimeZ	VVVeta	LLeta	VVVagm	LLagm	sfcInHt	sfcInSt	sqlInHt	sqlInSt	sfcCld%	sfcCldBs	sqlCld%	sqlCldBs	SolAng	sfcRad	sqlRad	funT
1996	148	12.8	-69	2	-41	3	250	12.6	?	?	0.38	884	?	?	9.9	?	?	10.7
1996	148	13.8	-69	2	-41	3	275	10	?	?	?	?	0.75	1524	21.3	?	?	10.8
1996	150	15.75	-29	6	-37	8	275	10	?	?	1	457	0.75	488	45.1	?	?	10.7
1996	150	16.75	-29	6	-37	8	300	8	?	?	1	518	0.75	488	56.7	?	?	11.4
1996	167	16.83	2	8	2	8	250	12.8	?	?	1	305	0.38	183	53.8	?	?	10
1996	167	17.83	2	8	2	8	300	10.9	?	?	1	366	0.38	183	68.4	?	?	10.4
1996	172	17.65	8	12	6	13	275	7.7	?	?	1	366	0.75	549	68.5	?	?	11.2
1996	172	18.65	8	12	6	13	275	10.8	?	?	1	427	0.75	549	75.4	?	?	11.2
1996	173	15.58	3	10	-22	9	275	9.7	?	?	1	396	0.38	488	43.2	?	?	10.7
1996	173	16.58	3	10	-22	9	250	13.9	?	?	1	396	0.38	488	55	?	?	11.1
1996	176	17.75	0	11	-14	11	275	12.4	?	?	?	?	?	?	68.5	?	?	?
1996	176	18.75	0	11	-14	11	300	10.3	?	?	?	?	?	?	75.4	?	?	11.7
1996	177	19.13	-6	6	-22	3	325	4.5	?	?	1	579	0.75	823	75.4	?	?	11.9
1996	177	20.13	-6	6	-22	3	300	8.2	?	?	1	518	0.75	914	68.5	?	?	12.6
1996	186	13.75	7	13	7	13	?	?	?	?	0.38	213	0.75	335	22.2	?	?	11.2
1996	186	14.75	7	13	7	13	?	?	?	?	1	396	0.75	335	34	?	?	11.1
1996	189	14.6	6	12	-9	6	1150	3.4	?	?	1	213	1	213	30.9	?	?	11.9
1996	189	15.6	6	12	-9	6	975	5.4	?	?	1	274	0.75	3657	42.8	?	?	11.9
1996	190	15.58	-6	10	-6	9	550	2.9	?	?	1	396	0.38	274	42.7	?	?	11.8
1996	190	16.58	-6	10	-6	9	1950	3.7	?	?	1	396	0.38	274	54.5	?	?	12.1
1996	191	15.17	4	10	-4	8	1475	2.5	?	?	1	213	1	304	39.7	?	?	12.2
1996	191	16.17	4	10	-4	8	1575	3.7	?	?	0.75	274	0.75	396	51.5	?	?	12.7
1996	192	16.33	-14	11	5	10	1525	4.5	?	?	1	274	0.75	335	51.4	?	?	12.1
1996	192	17.33	-14	11	5	10	1550	2.7	?	?	0.19	396	0.38	457	62.7	?	?	12.5
1996	193	14.75	6	5	-2	1	875	4.6	?	?	1	304	0.75	335	33.6	?	?	11.1
1996	193	15.75	6	5	-2	1	600	6.2	?	?	?	?	?	?	45.5	?	?	?
1996	195	14.3	18	7	-9	5	1275	3.7	?	?	0.75	274	1	243	27.5	?	?	11.2
1996	195	15.3	18	7	-9	5	1175	2.4	?	?	1	213	0.75	304	39.4	?	?	11.5
1996	196	15.42	-3	9	-1	8	1125	3.1	?	?	1	182	1	335	42.3	?	?	11.3
1996	196	16.42	-3	9	-1	8	900	5.7	?	?	0.75	243	?	?	54	?	?	11.4
1996	197	16.08	11	10	12	14	2025	1.8	?	?	1	274	?	?	48.1	?	?	12.9
1996	197	17.08	11	10	12	14	1925	4.1	?	?	1	335	?	?	59.5	?	?	13.1
1996	204	14.4	14	9	-23	8	1225	2.9	1250	7.9	?	?	0.75	182	29.6	129	164	11.5
1996	204	15.4	14	9	-23	8	1250	2.7	1200	7.2	0.75	182	0.38	182	41.5	232	99	11.4
1996	205	14.92	5	10	-28	6	850	3.3	225	13	?	?	?	?	0.38	213	106	12.8
1996	205	15.92	5	10	-28	6	800	4.9	250	8.8	?	?	0.19	213	47.3	449	375	12.9
1996	206	15.75	-15	8	-11	7	900	4	400	6	1	304	0.75	365	44.3	152	131	11.5
1996	206	16.75	-15	8	-11	7	900	4.3	400	6.5	?	?	0.38	365	55.7	603	610	11.8
1996	207	15.67	8	9	-5	6	625	4.3	1300	6.7	1	182	1	243	44.1	429	125	11.7
1996	207	16.67	8	9	-5	6	850	4.6	1300	7.4	1	243	0.75	335	55.6	325	397	12
1996	208	16.33	6	7	1	3	1575	2	225	5.3	0.75	304	0.75	335	49.8	426	539	11.9
1996	208	17.33	6	7	1	3	950	5.2	225	12.5	?	?	0.75	335	60.8	672	709	12.1
1996	220	17.5	-2	11	2	11	425	8.1	550	3.9	0.38	365	0.19	487	60.9	684	690	11.7
1996	220	18.5	-2	11	2	11	875	4.1	1625	2.8	?	?	?	?	67.7	823	820	12.2
1996	221	15.35	-18	10	3	8	1250	3.3	1175	7.3	1	213	?	?	42	360	311	11.8
1996	221	16.35	-18	10	3	8	1150	4.8	475	4.1	0.75	274	0.38	304	53.2	566	561	12
1996	228	16.17	-6	9	-5	7	1000	6.1	700	4.8	0.75	121	?	?	41.8	439	391	11.4
1996	228	17.17	-6	9	-5	7	975	8.1	3900	5.3	?	?	?	?	56.7	647	645	11.8
1996	230	15.83	?	?	-5	9	2000	3.5	1775	2.5	1	396	?	?	40.3	331	373	12.7
1996	230	16.83	?	?	-5	9	1850	5.8	225	10.4	0.19	396	?	?	51.3	532	320	12.9
1996	233	14.65	5	13	12	11	1975	2.3	450	3.7	1	335	?	?	28	108	107	?
1996	233	15.65	5	13	12	11	1725	2.8	250	10.4	1	335	?	?	39.7	185	368	11.9
1996	235	14.58	1	9	5	7	1300	2.3	250	9	0.75	213	0.75	274	24.7	35	32	?
1996	235	15.58	1	9	5	7	950	4	275	7.1	0.19	213	?	?	36.4	274	207	11.4
1996	237	16.53	4	12	13	10	975	2.5	1675	8.7	1	335	1	365	47	164	173	?
1996	237	17.53	4	12	13	10	1300	3.6	225	4.8	1	335	0.75	457	56.4	529	415	11.6
1996	238	16.57	-5	12	4	10	2350	3	425	8.4	1	487	?	?	46.7	153	203	?
1996	238	17.57	-5	12	4	10	2300	2.6	275	5.5	1	548	0.38	670	56.1	322	730	14.4
1996	239	17.33	3	9	23	9	725	2.8	3900	4.1	1	792	1	731	53.7	631	644	15
1996	239	18.33	3	9	23	9	775	3.8	300	6.3	0.75	853	1	731	60.6	365	416	15.3
1996	240	14.25	-31	13	-61	11	1250	4.3	3900	4.8	0.19	396	0.75	518	20.6	38	63	13.3
1996	240	15.25	-31	13	-61	11	1350	2.3	225	18	0.75	304	0.75	518	32.4	208	240	13.5
1996	246	15.37	7	13	-1	12	1825	2.9	200	26	1	426	1	274	30.9	106	85	12.4
1996	246	16.37	7	13	-1	12	1875	3.7	450	5.6	1	426	?	?	42	336	225	12.9
1996	247	17.12	28	13	2	14	2200	2.6	3900	5.1	1	487	?	?	49	560	556	13.1
1996	247	18.12	28	13	2	14	2150	2.5	250	7.8	1	609	0.75	609	56.5	543	762	13.5
1996	255	20.45	23	9	5	10	475	2.1	250	3.8	1	822	0.75	762	50.5	820	818	14.5
1996	255	21.45	23	9	5	10	425	7.2	300	5.8	0.75	883	0.75	1219	41.9	364	952	15.4
1996	257	16.37	-13	3	-7	4	875	3	250	4.9	1	243	?	?	38.8	414	430	14
1996	257	17.37	-13	3	-7	4	600	3.4	450	4	0.38	457	0.38	457	47.9	566	601	14.6
1996	259	19.92	6	5	12	4	425	4.8	375	5.3	0.19	304	0.75	396	52.1	801	810	16.5
1996	259	20.92	6	5	12	4	1025	2.3	575	2.9	0.38	548	0.38	457	45.2	666	774	?
1996	267	16	11	10	0	9	2000	2.9	400	7.5	1	396	1	304	33.3	112	205	12.1
1996	267	17	11	10	0	9	1925	4.6	225	21.2	0.38	548	1	396	42.5	524	278	13.2
1996	268	15.17	15	10	-20	10	2000	2.5	575	3.4	0.38	457	1	426	25.1	50	54	12
1996	268	16.17	15	10	-20	10	525	4.4	250	17	0.75	518	0.75	518	35.5	151	289	12.3
1996	269	17.48	5	10	-2	11	1300	2.9	3900	6.8	1	274	1	7620	45.5	276	305	11.2
1996	269	18.48	5	10	-2	11	900	3.8	525	6.4	?	?	1	7620	50	711	758	?
1996	270	17.37	-3	15	2	16	1600	3.9	375	5.5	1	304	?	?	43.4	293	347	11.6
1996	270	18.37	-3	15	2	16	575	5.2	500	4.4	0.38	365	0.38	914	48.9	675	706	12.1
1996	271	17.42	3	12	13	13	1950	3.4	250	12.8	1	457	?	?	44.7	430	332	12.8
1996	271	18.42	3	12	13	13	500	3.4	?	?	?	?	?	?	49.2	698	684	13.1
1996	272	16.87	12	11	5	10	1475	5.1	225	10.4	1	304	?	?	38.7	159	210	11.8
1996	272	17.87	12	11	5	10	825	2.6	725	5	0.38	365	0.75	304	45.9	624	668	11.7
1996	273	17.08	3	10	-1	9	1350	2.4	3900	5.1	1	152	?	?	40.4	127	148	11.2
1996	273	18.08	3	10	-1	9	1175	3.7	325	7.7	0.38	274	0.38	182	46.7	665	652	11.4
1996	274	20.13	12	6	3	6	2525	2.1	350	4.2	1	487	1	487	45.1	276	657	13.4
1996	274	21.13	12	6	3	6	600	2.9	725	3.5	?	?	?	?	38.1	?	?	13.4
1996	275	19.78	-24	6	-2	6	500	1.8	375	4.2	0.75	762	1	853	41.6	743	739	14.9
1996	275	20.78	-24	6	-2	6	525	3.6	225	12	1	731	0.75	975	41.6	817	497	?
1996	276	17.72	-7	6	-7	8	1750	3.1	3900	4	1	365	1	426	44.4	562	601	13.5
1996	276	18.72	-7	6	-7	8	1300	3	350	6.3	1	365	?	?	47.7	556	699	?
1996	277	16.08	-16	8	-13	8	1200	6.2	1175	9	1	182	?	?	30.3	293	291	11.6
1996	277	17.08	-16	8	-13	8	1075	3.9	350	7.1	1	243	?	?	39.1	562	515	11.7
1997	130	16.75	20	6	5	5	1800	3.3	?	?	1	213	1	426	54.1	214	392	10.6
1997	130	17.75	20	6	5	5	1650	1.9	?	?	0.75	396	0.38	457	63.9	321	750	11.1
1997	131	16.58	-28	6	-31	4	1775	2.9	?	?	1	213	0.38	396	51.6	610	631	10.9
1997	131	17.58	-28	6	-31	4	1525	3.2	?	?	1	274	0.38	396	61.9	309	756	11.1
1997	132	14.5	3	8	-13	8	1325	4.6	?	?	0.75	182	1	243	28.3	174	196	9.7
1997	132	15.5	3	8	-13	8	800	3	?	?	0.75	182	0.38	243	40.2	273	367	9.7
1997	134	14.47	-4	2	2	1	1450	4.6	?	?	0.38	274	0.19	243	28.6	206	207	13.5
1997	134	15.47	-4	2	2	1	1125	2	?	?	0.38	243	0.19	243	40.5	414	141	13.8
1997	143	18.83	19	2	-6	0	775	2.5	?	?	0.75	365	0.75	274	72.5	879	913	14.2
1997	143	19.83	19	2	-6	0	800	1.8	?	?	0.19	914	0.38	243	70.2	1087	664	15.5
1997	147	12	-40	4	-22	3	1050	3.9	?	?	0.75	152	?	?	1.6	0	0	15.1
1997	147	13	-40	4	-22	3	1025	3.3	?	?	0.75	152	?	?	12.6	5	5	14.9

Appendix B. Stratus burn-off training data set.

funTd	funWdd	funWdr	funWs	funTA	fundT	fundt	hwdT	hwdRH	hwdWdd	hwdWdr	hwdWs	hwdP	hwddP	hwdTA	nuqT	nuqRH	nuqWdd	nuqWdr
10	314	NW	4.1	0.2	0	-0.5	?	?	?	?	?	?	?	?	?	?	?	?
10.1	320	NW	4.1	0.4	0.1	0.5	12.2	84	?	?	0	?	?	5.7	?	?	?	?
9.3	297	NW	4.1	-2.2	0.7	1.5	12.2	?	240	SW	5.1	?	?	-0.2	?	?	?	?
9.7	286	W	4.1	-0.1	1.4	2.5	13.3	68	210	SW	3.6	?	?	4.7	?	?	?	?
8.8	260	W	5.1	-5.3	0.6	3.1	13.9	?	230	SW	5.1	?	?	0.7	?	?	?	?
8.9	245	SW	5.1	-4	1	4	14.4	73	230	SW	3.1	?	?	0.1	?	?	?	?
9.7	238	SW	7.7	3.9	0.6	4.9	?	?	?	?	?	?	?	?	?	?	?	?
9.6	245	SW	7.1	-1.6	0.6	6	14.4	76	270	W	6.2	?	?	0	?	?	?	?
9.1	295	NW	5.6	-0.2	0.9	1.8	12.8	?	250	W	5.1	?	?	1.6	?	?	?	?
9.2	286	W	6.1	-2.5	1.3	2.8	13.9	73	240	SW	3.6	?	?	2.8	?	?	?	?
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
11.7	226	SW	5.1	?	1.6	5.3	?	?	?	?	?	?	?	?	?	?	?	?
10.7	223	SW	3.1	-5.1	0.7	1.1	15	?	240	SW	4.1	?	?	0	?	?	?	?
11.1	241	SW	4.1	-1.5	1.4	2.3	16.7	68	290	W	5.1	?	?	-0.9	?	?	?	?
11.2	260	W	4.1	1	0.2	-0.8	?	?	?	?	?	?	?	?	16	88	30	NE
11.1	254	W	4.1	-2.4	0.1	0.3	14	88	270	W	2.6	1015.6	-0.3	0	16	82	?	?
11.6	204	SW	4.6	5.8	0.1	-0.7	15	82	330	NW	2.6	1012.9	-0.7	1.7	16	82	320	N
11.7	202	S	4.6	?	0.1	0.3	17	72	310	NW	2.6	1012.9	-0.3	?	17	82	?	?
11.6	203	SW	5.6	4	1	2.3	14	88	330	NW	2.6	1011.2	-0.7	0.9	16	82	120	SE
11.9	201	S	6.6	10.3	1.3	3.3	16	77	?	?	0	1011.2	-1	0	18	72	?	?
12.1	205	SW	3.1	-7.6	0.7	4.2	16	82	240	SW	2.6	1010.9	-0.4	-3.7	16	82	130	SE
12.3	199	S	4.6	-4.1	1.2	5.3	?	?	?	?	?	?	?	?	17	77	110	E
11.8	211	SW	5.1	7	0.5	1.6	17	77	?	?	0	1016.6	-0.6	-1	?	?	?	?
12.1	216	SW	4.6	11.7	0.9	2.5	17	77	?	?	0	1016.6	-0.6	0	19	73	360	N
11.1	223	SW	2.5	5	0.2	1.5	16	?	?	?	0	?	?	3.7	16	82	?	?
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
11.2	238	SW	4.1	4.6	0.1	0.6	14	88	330	NW	2.6	1014.3	-0.7	2.3	?	?	?	?
11.5	220	SW	2.5	4.8	0.4	1.5	17	72	310	NW	2.6	1014.9	-0.3	-0.2	16	88	330	NW
11.3	250	W	4.6	2.3	0	-0.1	15	88	330	NW	2.6	1014.3	-0.7	5.3	16	88	30	NE
11.4	238	SW	5.1	10.8	0.1	1	?	?	?	?	?	?	?	?	17	82	360	N
12.6	240	SW	4.1	-1.6	0.5	5.6	15	82	310	NW	4.1	1015.6	0	0	16	82	?	?
12.8	243	SW	4.6	8.3	0.7	6.5	?	?	?	?	?	?	?	?	17	77	?	?
11.5	212	SW	3.6	1.4	0.2	-1.6	15	82	310	NW	2.6	1018.3	-0.7	4.1	?	?	?	?
11.4	214	SW	3.6	0.3	0.1	-0.5	16	82	310	NW	2.6	1018.7	-0.7	-3.4	?	?	?	?
12.8	249	W	3.6	3.8	0.2	1.4	15	88	310	NW	2.6	1020	-1	0	17	82	360	N
12.9	252	W	3.6	9.2	0.3	2.5	16	82	330	NW	2.6	1020	-0.7	0	17	82	?	?
11.5	250	W	3.1	7.1	0.3	1.3	16	82	?	?	0	1017.3	0	6	?	?	?	?
11.7	263	W	3.6	9.1	0.6	2.3	17	77	300	NW	3.1	1017.3	-0.3	5.2	18	77	10	N
11.7	268	W	3.1	1.5	?	?	15	88	260	W	2.1	1014.6	-0.3	0.3	16	88	?	?
12	259	W	3.1	4.4	?	?	16	88	310	NW	3.1	1014.3	0	0.8	18	77	30	NE
11.9	247	SW	4.1	8.1	0.7	6.1	17	77	300	NW	2.6	1015.3	-0.4	1.2	16	82	340	N
12.1	242	SW	4.6	12	0.9	7	19	68	320	NW	2.1	1015.6	-0.7	6.8	19	73	?	?
11.6	241	SW	3.6	-1.5	0.3	1.3	19	68	330	NW	2.6	1017.3	-0.3	-2.5	18	77	340	N
11.7	244	SW	4.1	12	0.8	2.3	20	64	330	NW	4.1	1017	-0.4	7.7	19	73	360	N
11.8	276	W	?	6.4	0.6	4.9	?	?	?	?	?	?	?	?	15	88	20	N
12	231	SW	2.5	-1.3	0.8	6.3	16	82	?	?	0	1017.6	-0.3	0	16	82	?	?
11.4	198	W	3.1	2.5	0.2	2.2	?	?	?	?	?	?	?	?	17	88	?	?
11.8	202	S	4.1	5.1	0.6	3.3	?	?	?	?	?	?	?	?	?	?	?	?
12.2	200	S	5.1	3.2	1.1	3.3	?	?	?	?	?	?	?	?	?	?	?	?
12.3	215	SW	6.1	1.1	1.3	4.3	?	?	?	?	?	?	?	?	17	77	?	?
?	?	?	?	?	?	0.7	?	?	?	?	?	?	?	?	14	82	130	SE
11	258	W	3.6	-1.6	0.3	1.8	?	?	?	?	?	?	?	?	16	72	?	?
?	?	?	?	?	?	4.1	?	?	?	?	?	?	?	?	15	88	?	?
11.4	199	S	5.1	3.9	0.9	5	15	82	320	NW	2.6	1014.3	-0.4	-1.3	?	?	?	?
?	?	?	?	?	?	11.5	15	82	330	NW	4.1	1016	-0.7	1.2	16	88	350	N
11.6	238	SW	3.6	10.6	1.2	12.5	16	77	?	?	?	1016	-0.4	?	17	77	330	NW
?	?	?	?	?	?	11.3	17	72	310	NW	3.6	1015.6	-0.7	0	18	68	?	?
14.1	209	SW	3.1	12.9	1	12.3	18	68	330	NW	4.1	1015.6	-0.7	0	18	72	40	NE
14.4	206	SW	4.6	9.4	2.9	13.3	18	72	330	NW	2.6	1012.9	-0.7	0	?	?	?	?
14.3	203	SW	4.6	11.5	3.2	14	18	72	330	NW	2.6	1012.9	-0.7	-3.8	19	58	?	?
13.3	234	SW	3.1	4	0.1	4.5	16	82	300	NW	4.1	1013.9	-0.3	0.9	16	77	260	W
13.5	244	SW	2.5	4.3	0.3	5.5	16	82	320	NW	2.6	1014.3	-0.7	0	16	82	?	?
11.4	188	S	3.6	1.2	0.3	1.4	15	77	160	S	3.1	1011.5	0	1.3	13	88	140	SE
11.7	198	S	4.1	2.7	0.8	2	17	68	200	S	2.1	1011.9	-0.4	-2	16	77	?	?
12.2	201	S	4.6	?	0.3	1.4	16	77	330	NW	2.6	1013.9	0	?	14	88	?	?
12	208	SW	4.6	-3.1	0.7	2.3	17	72	230	SW	3.6	1014.3	-0.4	0	17	77	?	?
13.8	200	S	4.6	?	2.8	14.5	19	64	250	W	3.6	1015.3	-0.4	?	?	?	?	?
13.9	215	SW	5.1	23.5	3.7	15.5	19	64	320	NW	5.1	1014.6	0	-3.5	21	56	350	N
14	284	W	5.1	0.6	0.1	2.9	16	94	331	NW	0.5	1010.5	0.4	0	18	72	300	NW
14	269	W	3.1	8	0.7	3.8	17	77	330	NW	5.1	1011.2	-0.3	0	19	64	300	NW
16.5	227	SW	4.1	19	?	?	20	83	320	NW	5.1	1012.9	-0.3	-4.6	22	69	290	W
?	?	?	?	?	?	?	20	73	310	NW	5.1	1012.9	-0.3	-6.3	23	60	290	W
11.1	206	SW	7.7	2.1	0.2	0.3	15	82	?	?	0	1015.3	0	1.3	?	?	?	?
11.4	209	SW	7.1	2.4	1.3	1.5	15	82	?	?	0	1016	-0.4	0	?	?	?	?
10.5	239	SW	4.1	1.7	1.8	7.2	13	88	270	W	2.6	1016.6	-0.6	0	14	82	310	NW
10.7	214	SW	3.6	7.2	2.1	8	?	?	?	?	?	?	?	?	14	82	60	NE
11.2	235	SW	2.5	-0.8	0.7	2.2	17	77	?	?	0	1016	-0.7	-0.5	17	77	350	N
?	?	?	?	?	?	?	18	72	280	W	4.6	1015.6	-0.3	-4.3	19	68	360	N
10.8	229	SW	1.5	?	0.7	2.1	17	72	?	?	0	1016	-0.7	?	14	88	110	E
11.3	216	SW	3.6	-2.5	1.2	2.8	17	72	?	?	0	1016	-0.7	-2.2	18	68	?	?
11.4	213	SW	3.1	0.4	0.6	3.4	?	?	?	?	?	?	?	?	16	77	?	?
11.6	234	SW	3.1	-0.1	0.9	4	18	68	280	W	3.1	1018.3	-0.7	-3.6	19	64	?	?
11	303	NW	2	3	0.7	7.9	15	82	280	W·	2.6	1020.4	-0.4	-0.4	14	88	330	NW
11	293	NW	1.5	?	0.6	8.8	16	77	280	W	2.6	1020.4	-0.4	?	16	77	?	?
11.2	222	SW	3.6	-2.6	0.5	1.8	14	88	?	?	0	1016	-0.7	0	15	88	?	?
11.4	272	W	4.1	16.2	0.7	2.8	16	82	?	?	0	1015.6	-0.7	0	17	77	20	N
13.2	217	SW	4.6	11.2	1.9	9.4	17	72	250	W	2.6	1012.6	-0.7	0	17	72	?	?
13.2	217	SW	5.1	8	1.9	10.5	?	?	?	?	?	?	?	?	?	?	?	?
14.1	208	SW	4.6	-2.9	1.2	4.3	20	60	?	?	0	1013.9	0	5.5	21	56	?	?
?	?	?	?	?	?	?	20	64	200	S	7.7	1013.9	-0.3	1.6	21	60	350	N
12.3	262	W	3.1	1	1.2	6.2	15	88	270	W	2.6	1018.3	-0.7	0	?	?	10	N
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
11.6	228	SW	2	?	0.2	0.8	14	88	?	?	0	1018.3	-0.7	?	15	82	?	?
11.7	209	SW	1.5	-1	0.3	2	16	82	?	?	0	1018	-0.7	-2.8	16	77	?	?
10.5	260	W	3.6	1.5	0.5	1.3	14	82	260	W	3.6	1018.3	0	3	15	72	?	?
11.1	218	SW	3.1	6.9	1	2.3	13	88	300	NW	4.1	1018.3	-0.3	0	17	68	40	NE
10.7	286	W	2.5	-2.4	0.6	2.3	13	88	290	W	2.6	1017.3	-0.3	-0.7	15	77	360	N
10.8	264	W	3.1	0.1	0.8	3.5	15	82	270	W	4.1	1017.3	-0.3	-3.2	17	68	?	?
9.7	243	SW	3.6	2.6	0.1	-2	13	94	?	?	0	1015.6	-0.3	2.9	14	82	?	?
9.7	259	W	3.6	0.3	0.1	-1	14	88	?	?	0	1015.6	-0.3	4	16	77	350	N
13.5	241	SW	1.5	6	0.1	0.5	18	94	250	W	2.6	1016.3	-0.7	-0.1	18	88	350	N
13.8	244	SW	1.5	9.2	0.4	1.5	18	88	250	W	3.1	1016.3	-0.7	-0.7	20	78	?	?
13.9	325	NW	3.1	-7.6	1.7	2.6	17	88	240	SW	2.6	1017.3	-0.3	0	17	88	130	SE
15	259	W	2.5	-2.5	3	3.5	19	83	?	?	0	1017.3	-0.3	-1.3	19	83	60	NE
15.1	4	N	0.5	1.6	0.8	7.3	?	?	?	?	?	?	?	?	18	88	?	?
14.9	81	E	1	0	0.6	8.3	?	?	?	?	?	?	?	?	18	83	?	?

Appendix B. Stratus burn-off training data set.

nuqWs	nuqP	nuqdP	nuqTA	nuqdT	nuqdt	oakT	oakRH	oakWdd	oakWdr	oakWs	oakP	paoT	paoRH	paoWdd	paoWdr	paoWs	paoP	rhvT
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
?	?	?	?	?	?	12.2	?	210	SW	4.1	?	12.2	?	?	?	0	?	12.8
?	?	?	?	?	?	11.7	?	200	S	6.2	?	12.8	?	?	?	0	?	14.4
?	?	?	?	?	?	13.3	?	190	S	4.1	?	14.4	?	170	S	2.6	?	15.6
?	?	?	?	?	?	12.2	?	200	S	5.1	?	15	?	290	W	3.6	?	15.6
?	?	?	?	?	?	15	?	230	SW	5.1	?	16.1	?	360	N	3.1	?	17.2
?	?	?	?	?	?	13.9	?	260	W	7.2	?	16.7	?	290	W	5.1	?	17.2
?	?	?	?	?	?	14.4	?	240	SW	5.1	?	17.8	?	320	NW	7.7	?	19.4
?	?	?	?	?	?	13.3	?	180	S	5.1	?	15.6	?	?	?	0	?	16.1
?	?	?	?	?	?	13.9	?	200	S	5.1	?	15.6	?	240	SW	2.6	?	17.2
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
?	?	?	?	?	?	15.6	?	250	W	5.1	?	16.1	?	210	SW	4.1	?	17.2
?	?	?	?	?	?	15.6	?	240	SW	5.1	?	18.3	?	10	N	4.6	?	18.9
1.5	1015.3	-0.4	16.4	0	3.83	14	94	320	NW	2.1	1014.9	15	88	?	?	0	1015.3	15
0	1015.3	0	3.5	0	4.83	14	94	?	?	1.5	1015.6	16	88	10	N	3.6	1015.6	?
1.5	1012.6	-0.4	0.9	1	1.68	15	82	350	N	3.6	1012.9	16	82	270	W	1.5	1012.9	?
0	1012.6	0	?	2	2.68	17	77	270	W	2.6	1012.9	17	82	40	NE	2.6	1012.9	16
2.6	1010.9	-0.4	2.6	1	1.66	?	?	?	?	?	?	17	77	?	?	2.1	1010.5	16
1.5	1010.5	-0.3	?	3	2.66	16	82	230	SW	2.1	1010.9	18	77	?	?	3.1	1010.5	18
2.6	1010.5	0	-0.6	1	1.25	16	88	230	SW	2.1	1010.9	17	77	?	?	0	1010.5	15
1.5	1010.9	0	-1.1	2	2.25	?	?	?	?	?	?	?	?	?	?	?	?	?
?	?	?	?	?	3.41	16	82	270	W	3.6	1016.6	18	77	360	N	4.1	1016	?
3.1	1016	0	1.5	4	4.41	16	82	270	W	3.6	1016.6	18	77	360	N	4.1	1016	21
0	1017	0	4.1	?	?	14	88	340	N	2.1	1017.3	15	88	330	NW	2.6	1017	17
?	?	0	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
?	?	?	?	?	-0.62	?	?	?	?	?	?	16	88	330	NW	3.1	1014.3	17
2.6	1014.3	0.3	-0.5	0	0.38	14	88	320	NW	5.1	1014.6	16	82	350	N	3.1	1014.6	19
2.6	1013.6	0	11.4	0	-0.5	14	94	280	W	2.6	1014.3	16	88	?	?	0	1014.3	17
2.6	1013.9	0	?	1	0.5	14	94	280	W	3.6	1014.6	?	?	?	?	?	?	?
2.1	1015.6	0	?	0	0.16	14	94	270	W	3.1	1016	16	82	330	NW	3.6	1015.6	16
1.5	1015.6	-1.7	?	1	1.16	15	88	260	W	3.1	1016	?	?	?	?	?	1015.6	?
?	?	?	?	?	2.48	14	94	330	NW	3.1	1018.3	16	88	330	NW	2.6	1017.6	18
?	?	?	?	?	3.48	16	82	330	NW	3.1	1018.3	17	82	?	?	0	1017.6	19
3.1	[illegible]	-0.3	4	1	1	15	88	280	W	2.6	1019.3	17	82	330	NW	3.6	1019.3	17
0	1019.7	-0.4	5.1	1	2	16	82	280	W	2.6	1020	17	88	20	N	4.1	1019.3	20
?	?	?	?	?	3.83	14	88	300	NW	2.6	1017.6	?	?	?	?	?	?	18
2.6	1017	0	13.4	3	4.83	16	82	300	NW	4.1	1017.6	17	77	300	NW	3.1	1017	20
0	1014.3	0	6.2	?	?	14	94	360	N	2.6	1014.9	16	88	350	N	2.6	1012.9	?
3.6	1014.3	0	10	?	?	15	88	?	?	0	1014.6	17	82	?	?	?	1013.9	?
3.1	1015.3	-0.4	0	1	2.41	15	88	300	NW	2.6	1015.6	16	88	?	?	0	1015.3	18
1.5	1015.3	-0.4	?	4	3.41	17	77	320	NW	3.6	1016	18	77	20	N	2.6	1015.6	22
3.6	1017	0	-1.7	4	8.58	14	94	300	NW	4.1	1017.6	18	77	?	?	2.1	1016	21
3.6	1016.6	0	4.9	5	9.58	17	77	290	W	3.1	1017.3	19	68	20	N	4.6	1016	24
2.1	1017.6	-0.3	2.5	1	1.43	?	?	?	?	?	?	?	?	?	?	?	?	?
1.5	1017.3	0	?	2	2.43	14	94	240	SW	3.6	1017.6	16	82	?	?	0	1017.3	17
0	1016.3	?	0	?	?	16	?	240	?	2.1	1016.3	16	88	?	?	0	1016.3	19
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
1.5	1015.6	-0.3	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
1.5	1018.7	-0.7	1.2	2	2.73	?	?	?	?	?	?	?	?	?	?	?	?	?
0	1018.7	0	3.6	4	3.73	?	?	?	?	?	?	?	?	?	?	?	?	?
0	1014.3	-0.4	?	1	0.66	13	100	?	?	0	1014.6	15	88	?	?	0	1014.6	14
?	?	?	?	?	1.66	14	94	240	SW	1.5	1014.3	15	88	?	?	2.6	1014.6	15
2.1	1015.6	-0.3	5.2	2	3.61	13	100	320	NW	3.6	1016.3	15	88	30	NE	3.1	1015.6	18
2.6	1015.6	0	4.2	3	4.61	14	94	270	W	2.6	1016.3	16	82	30	NE	3.1	1016	20
1.5	1015.3	-0.4	?	2	0.65	?	?	?	?	?	?	17	72	350	N	3.1	1014.9	18
2.6	1014.9	0	0	2	1.65	16	88	260	W	3.6	1015.6	19	68	330	NW	4.1	1014.6	19
?	?	?	?	?	7.41	?	?	?	?	?	?	?	?	?	?	?	?	?
2.6	1012.2	0	?	4	8.41	17	82	230	SW	3.1	1012.6	19	68	10	N	3.1	1012.6	20
1.5	1013.9	-0.3	2.3	2	2.33	15	100	290	W	4.6	1013.9	13	88	?	?	0	1013.6	13
0	1014.3	-0.7	0	2	3.33	16	88	220	SW	3.6	1014.3	16	77	?	?	2.1	1013.9	15
4.1	1011.5	0	-3.1	1	1.45	15	88	240	SW	2.6	1011.5	14	82	140	SE	3.6	1011.5	12
0	1011.9	-0.4	0	4	2.45	16	82	110	E	1.5	1011.9	16	77	80	E	3.1	1011.9	16
1.5	1013.9	0	?	0	0.2	15	88	210	SW	2.1	1014.3	16	82	140	SE	3.1	1013.9	17
0	1013.9	0	0	3	1.2	16	82	250	W	2.1	1014.6	18	72	90	E	3.6	1014.3	19
?	?	?	?	?	6.53	18	68	250	W	4.1	1015.3	20	56	210	SW	4.6	1012.9	?
5.7	1014.3	0.3	1.2	7	7.53	19	68	270	W	5.1	1014.9	20	64	350	N	6.7	1014.3	22
3.1	1010.9	0	4.1	1	1.45	16	88	280	W	5.7	1011.5	18	72	290	W	4.1	1011.2	?
5.7	1011.2	-0.3	0.6	2	2.45	18	83	270	W	5.1	1011.5	19	68	330	NW	6.2	1011.2	18
3.6	1012.6	0	1.7	5	6	19	88	260	W	6.2	1013.2	22	69	330	NW	4.1	1012.2	19
4.1	1012.6	0	8.3	6	?	21	78	260	W	6.2	1013.2	20	?	330	NW	7.7	?	22
?	?	?	?	?	?	14	88	290	W	2.1	1015.3	15	77	140	SE	2.1	1015.6	14
?	?	?	?	?	?	14	88	210	SW	3.6	1016.3	16	77	40	NE	2.6	1016	15
3.1	1016	0	0.3	1	1.25	13	88	280	W	4.1	1017	14	77	320	NW	4.1	1019	12
2.1	1016.6	0	0	1	2.25	13	88	280	W	4.1	1017	14	77	310	NW	2.6	1016.6	13
2.1	1015.3	0	-0.8	5	3.65	14	88	310	NW	2.1	1016	16	82	?	?	2.1	1014.9	18
3.1	1014.9	0.4	0.1	7	4.65	17	82	290	W	2.6	1015.6	18	77	20	N	4.6	1014.9	?
1.5	1015.6	-0.3	?	0	0.45	15	82	350	NW	2.6	1016	16	77	?	?	2.1	1015.3	15
1.5	1014.9	0.4	?	4	1.45	19	68	250	W	3.1	1015.6	17	77	30	NE	3.1	1014.9	17
0	1017.6	0	0	2	2.5	?	?	?	?	?	?	?	?	?	?	?	?	?
2.6	1017.6	0	?	5	3.5	19	68	240	SW	3.1	1018	18	72	?	?	3.1	1018	17
1.5	1020	0	1.2	1	5.95	13	88	260	W	2.6	1020.4	15	82	330	NW	2.6	1020.7	14
2.1	1020	0	?	3	6.95	16	72	270	W	3.6	1020.4	16	77	?	?	3.6	1020.4	16
0	1015.3	0	-2.1	1	1.16	13	94	180	S	2.1	1015.6	15	88	50	NE	2.6	1015.6	14
2.1	1014.9	0	6.5	3	2.16	13	94	?	?	0	1015.6	15	88	40	NE	2.1	1015.3	?
1.5	1011.9	0	?	3	3.21	16	82	250	W	3.1	1012.6	17	77	50	NE	3.6	1012.2	17
?	?	?	?	?	4.21	?	?	?	?	?	?	?	?	?	?	?	?	?
1.5	1013.2	0.7	?	5	4.86	19	64	240	SW	2.6	1014.6	20	60	360	N	6.2	1013.6	22
7.2	1013.2	0.4	-6.9	5	5.86	?	?	?	?	?	?	?	?	?	?	?	?	22
2.6	1017.6	0	?	?	?	15	88	290	W	3.1	1018.3	16	82	?	?	2.1	1018.7	17
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
0	1017.6	0	?	1	1.16	14	88	290	W	1	1018	15	82	?	?	0	1017.3	13
2.1	1017.6	-0.3	?	2	2.16	15	88	270	W	1.5	1018	16	82	?	?	0	1017.3	14
1.5	1018	0.3	?	2	1.83	13	77	230	SW	3.6	1018.3	15	?	20	N	1.5	?	16
2.6	1017.6	0.4	16.3	4	2.83	14	72	270	W	3.6	1018.3	17	68	310	NW	5.1	1017.3	18
1.5	1017	0	-1.9	2	4.66	14	72	?	?	0	1017.3	15	77	330	NW	1.5	1017	15
2.1	1017	0	?	4	5.66	15	67	260	W	3.1	1017.6	?	?	?	?	?	?	18
0	1015.3	0	5.7	1	1.58	13	82	70	E	1.5	1015.6	14	88	?	?	0	1015.3	14
1.5	1015.3	0	6.2	3	2.58	14	77	?	?	?	1015.6	15	88	?	?	0	1015.3	16
1.5	1016	-0.4	1.3	0	-0.45	18	77	280	W	3.1	1016	18	88	30	NE	1.5	1015.6	18
1.5	1016	-0.4	?	2	0.55	18	77	240	SW	2.6	1016.3	19	83	10	N	2.6	1016	20
3.6	1017.3	-0.3	0	?	1.91	17	77	120	SE	3.1	1017.3	17	88	150	SE	3.6	1016.6	16
1.5	1017	0	1.3	4	2.91	19	73	180	S	3.6	1017.6	19	83	80	E	4.1	1016.6	18
0	1021	-0.3	4.1	0	-1.92	18	83	270	W	2.6	1021.4	?	?	?	?	?	?	?
0	1020.7	0	0	0	-0.92	?	?	280	W	2.6	?	?	?	?	?	?	?	?

Appendix B. Stratus burn-off training data set.

rhvRH	rhvWdd	rhvWdr	rhvWs	rhvP	sfoT	sfoRH	sfoWdd	sfoWdr	sfoWs	sfoP	sfodT	sfodt	sjcT	sjcRH	sjcWdd	sjcWdr	sjcWs	sjcP
?	?	?	?	?	10.6	89	250	W	4.1	1014.3	0	-1.3	12.2	?	0	N	0	?
?	?	?	0	?	10.6	89	250	W	3.6	1014.6	0	-0.3	15.6	?	?	?	0	?
?	130	SE	4.1	?	11.7	74	240	SW	4.6	1014.1	1.7	2.1	15	?	180	S	4.1	?
?	140	SE	5.1	?	12.2	71	250	W	6.7	1014.4	2.2	3.1	16.7	?	190	S	2.6	?
?	?	?	0	?	11.7	83	220	SW	6.2	1015.1	1.1	1.7	16.7	?	80	E	2.1	?
?	150	SE	4.1	?	12.2	80	220	SW	3.6	1015	1.6	2.7	18.3	?	?	?	0	?
?	320	NW	5.1	?	12.8	80	260	W	7.7	1014.7	1.7	4.2	18.9	?	330	NW	3.6	?
?	320	NW	4.1	?	14.4	75	240	SW	7.2	1014.5	3.3	5.2	20	?	300	NW	3.6	?
?	240	SW	3.1	?	12.2	80	260	W	7.7	1011.5	1.1	1.2	16.1	?	360	N	2.1	?
?	?	?	0	?	13.3	75	250	W	8.2	1011.9	2.2	2.2	18.3	?	50	NE	1.5	?
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
?	280	W	2.6	?	15	72	200	S	4.6	1013	2.2	4.1	18.3	?	?	?	0	?
?	?	?	0	?	15	72	230	SW	4.6	1012.8	2.2	5.2	20	?	?	?	0	?
88	?	?	0	1015.3	12	100	280	W	4.6	1014.9	0	-0.3	17	77	?	?	0	1015.3
?	280	W	2.6	?	14	88	270	W	2.1	1015.3	2	0.8	17	82	30	NE	1.5	1015.6
?	?	?	0	1013.2	14	88	263	W	2.6	1012.2	2	1	15	82	?	?	0	1012.6
68	?	?	0	1013.2	15	82	?	?	2.6	1012.6	3	2	19	68	?	?	0	1012.9
77	130	SE	3.6	1011.2	15	82	?	?	0	1010.5	2	1	16	82	190	S	3.1	1011.2
68	220	SW	2.6	1010.9	16	77	10	N	2.1	1010.2	3	2	18	72	170	S	2.6	1010.9
77	190	S	2.6	1010.9	15	82	150	SE	3.6	1010.5	3	4.3	16	77	140	SE	4.1	1011.2
?	?	?	?	?	16	82	120	SE	2.6	1010.9	4	5.2	?	?	?	?	?	?
?	?	?	?	?	16	82	10	N	3.1	1016	3	6.6	?	?	?	?	?	?
56	?	?	0	1016	17	77	350	N	3.6	1016	4	7.6	21	60	?	?	0	1016.3
72	?	?	0	1017.6	14	88	290	W	2.1	1017	2	1.5	17	77	?	?	0	1017.6
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
77	?	?	0	1014.3	13	94	300	NW	4.1	1013.6	1	0.4	18	77	340	N	2.1	1014.3
68	?	?	0	1014.9	14	88	300	NW	2.1	1014.6	2	1.5	?	?	?	?	?	?
82	?	?	0	1013.9	13	94	290	W	4.1	1013.6	0	-0.3	18	77	?	?	0	1014.3
?	?	?	?	?	15	82	290	W	5.1	1013.9	2	0.8	18	77	330	NW	2.1	1014.3
72	350	N	3.1	1016	14	88	220	SW	3.6	1015.6	1	0.4	18	72	330	NW	2.1	1016
?	?	?	0	1016	15	82	290	W	6.7	1013.9	2	1.4	18	72	?	?	0	1016
77	?	?	0	1018	12	100	270	W	3.1	1017.6	0	0	19	77	?	?	0	1018.3
73	?	?	0	1018	14	88	?	?	0	1018	2	1	20	78	?	?	0	1018.3
45	310	NW	2.6	1019.7	15	88	280	W	4.1	1019	2	1.8	18	77	?	?	0	1019.7
30	?	?	0	1019.7	16	82	300	NW	5.1	1019.3	3	2.8	19	77	?	?	0	1020
?	130	SE	2.1	1017.6	14	88	310	NW	4.6	1017.3	2	7.1	19	73	?	?	0	1017.6
26	280	W	2.1	1017	15	82	290	W	5.7	1017	3	8.1	20	68	?	?	0	1017
?	?	?	?	?	14	88	300	NW	3.1	1014.3	?	?	?	?	?	?	?	?
?	?	?	?	?	15	82	300	NW	3.6	1014.3	?	?	20	78	?	?	0	1014.3
77	?	?	0	1015.3	16	77	300	NW	4.1	1014.9	4	3.5	20	78	?	?	0	1015.3
64	350	N	4.1	1014.9	16	82	310	NW	5.1	1014.9	4	4.5	20	78	?	?	0	1015.6
60	290	W	2.6	1017	17	77	360	N	2.1	1017	5	7.8	20	68	?	?	0	1017.3
50	280	W	2.1	1016.6	17	72	290	W	4.6	1016.6	5	8.8	21	64	320	NW	3.1	1016.6
?	?	?	?	?	14	88	270	W	3.6	1017.3	2	0.9	?	?	?	?	?	?
77	230	SW	2.6	1018	14	88	?	?	0	1017.3	2	2.3	17	77	?	?	0	1017.6
73	?	?	0	1016.3	14	94	?	?	0	1016	3	2.3	18	83	?	?	0	1016
?	?	?	?	?	16	82	30	NE	2.1	1016	5	3.3	?	?	?	?	?	?
?	?	?	?	?	15	82	?	?	0	1015.3	3	5.8	?	?	?	?	?	?
?	?	?	?	?	17	72	30	NE	1.5	1015.3	5	6.8	?	?	?	?	?	?
?	?	?	?	?	13	88	210	SW	4.6	1018	0	-0.9	?	?	?	?	?	?
?	?	?	?	?	14	82	240	SW	4.1	1018.7	1	0.2	?	?	?	?	?	?
94	280	W	2.6	1014.6	13	88	?	?	1.5	1013.9	2	1.3	15	88	?	?	0	1014.6
88	?	?	2.1	1014.6	14	88	?	?	0	1013.9	3	2.3	15	88	?	?	0	1014.6
72	?	?	0	1016	14	88	310	NW	4.1	1015.3	2	2	18	77	340	N	2.1	1016
64	200	S	2.1	1016	15	82	320	NW	4.6	1015.6	3	2.9	?	?	?	?	?	?
68	?	?	0	1015.3	17	72	270	W	5.1	1014.9	3	9.2	?	?	?	?	?	?
64	?	?	0	1015.3	18	68	260	W	4.6	1014.9	4	10.3	19	68	10	N	3.1	1015.3
?	?	?	?	?	18	63	240	SW	5.7	1012.2	5	11.3	?	?	?	?	?	?
64	250	W	3.1	1012.9	19	64	240	SW	5.1	1012.2	6	12.3	?	?	?	?	?	?
82	?	?	0	1014.3	15	88	270	W	4.1	1013.6	1	3.8	16	72	?	?	0	1013.9
77	?	?	2.1	1014.6	16	88	270	W	3.6	1013.6	2	4.8	16	77	300	NW	2.1	1014.6
94	?	?	0	1012.2	14	82	190	S	2.1	1011.5	1	0.5	13	88	160	S	4.1	1012.2
72	10	N	3.6	1012.6	15	77	?	?	0	1011.5	2	1.5	16	77	130	SE	2.6	1012.2
68	100	E	2.6	1014.3	16	77	?	?	1.5	1013.9	2	1.5	14	88	180	S	3.1	1014.3
64	?	?	2.1	1013.9	17	72	180	S	2.6	1013.9	3	2.5	18	68	?	?	0	1014.3
?	?	?	?	?	18	63	?	?	2.6	1014.9	5	8.5	20	60	20	N	2.1	1015.3
49	290	W	5.1	1013.9	20	56	270	W	6.2	1014.6	7	9.4	21	56	?	?	2.6	1014.3
?	?	?	?	?	16	88	270	W	6.2	1010.9	2	2.4	18	77	?	?	0	1010.9
77	320	NW	7.7	1011.5	17	77	270	W	7.2	1010.9	3	3.3	19	73	?	?	?	1011.5
88	330	NW	4.1	1013.2	21	68	260	W	7.2	1012.6	5	14.8	24	65	330	NW	4.6	1012.9
78	360	N	5.1	1012.6	21	68	270	W	9.8	1012.6	5	15.8	24	65	330	NW	5.1	1012.6
82	160	S	3.6	1016	14	82	210	SW	2.1	1015.3	2	1	13	88	150	SE	3.6	1016
77	200	S	4.1	1016.3	16	72	?	?	0	1015.6	4	2	13	88	150	SE	3.6	1016.6
82	?	?	0	1016.6	13	77	270	W	4.1	1016	2	3.4	?	?	?	?	?	?
82	?	?	0	1017.3	14	72	270	W	5.1	1016.6	3	4.4	13	88	?	?	0	1017
63	?	?	0	1015.6	16	82	10	N	1.5	1015.3	5	7.7	20	60	?	?	0	1015.6
?	?	?	?	?	17	77	350	N	2.6	1015.3	6	8.8	23	43	300	NW	2.1	1015.3
77	?	?	0	1016.3	14	88	?	?	1.5	1015.3	3	8.5	?	?	?	?	?	?
68	?	?	0	1015.6	16	77	50	NE	2.6	1015.3	5	9.4	14	82	?	?	0	1015.6
?	?	?	?	?	15	82	?	?	0	1017.6	3	4.9	?	?	?	?	?	?
72	230	SW	2.1	1018.7	17	72	10	N	2.1	1017.6	5	5.9	19	64	70	E	1.5	1018.3
88	?	?	0	1020.7	13	88	290	W	2.6	1020	2	3.1	15	82	?	?	0	1020.7
77	?	?	0	1020.4	15	77	?	?	2.6	1020	4	4.1	13	94	330	NW	2.1	1020.4
88	?	?	0	1016	13	94	170	S	1.5	1015.3	1	1	14	94	?	?	0	1016
?	?	?	?	?	16	77	280	W	7.7	1014.9	4	2	16	82	?	?	0	1015.3
77	250	W	3.1	1012.6	17	72	250	W	5.7	1011.9	5	11	18	68	?	?	0	1012.9
?	?	?	?	?	17	72	240	SW	5.7	1011.5	5	11.7	?	?	?	?	?	?
46	?	?	0	1013.9	18	68	200	S	5.7	1013.9	2	3.1	23	46	?	?	0	1013.6
46	350	N	4.1	1013.2	18	68	250	W	4.6	1013.6	2	4.1	18	68	250	W	4.6	1013.6
72	?	?	2.1	1018.3	15	82	270	W	3.6	1017.6	3	5.6	18	68	350	N	2.1	1018
?	?	?	?	?	16	77	290	W	4.1	1017.6	4	6.7	?	?	?	?	?	?
94	?	?	2.1	1018	13	94	?	?	1.5	1017.6	1	2.8	15	88	?	?	0	1018
88	?	?	2.1	1018	14	88	60	NE	1.5	1017.3	2	3.8	17	77	?	?	0	1018
72	?	?	0	1017	12	88	260	W	5.1	1018.3	0	-0.1	14	88	?	?	0	1018.3
63	260	W	2.6	1018	13	88	270	W	4.6	1018	1	0.9	16	72	330	NW	2.1	1018
77	?	?	0	1017.6	12	94	220	SW	2.1	1017	0	-0.1	16	72	?	?	0	1017.3
63	?	?	0	1017	13	88	280	W	2.6	1017	1	0.9	17	72	360	N	3.6	1017.3
88	?	?	0	1015.6	12	94	280	W	3.1	1015.3	1	0.3	15	88	?	?	0	1016
77	?	?	0	1015.6	12	94	300	NW	2.6	1015.3	1	1.3	16	82	?	?	0	1015.6
88	?	?	0	1016.3	17	88	280	W	2.6	1015.6	1	0.1	18	77	?	?	0	1016.3
73	310	NW	5.1	1016.3	17	88	310	NW	3.6	1015.6	1	1.2	19	83	?	?	0	1016.3
94	190	S	2.6	1017.6	17	94	30	NE	2.1	1017	2	2.2	18	83	160	S	2.6	1017.6
88	150	SE	2.1	1017.6	18	88	20	N	2.6	1017	3	3.2	18	88	?	?	0	1017.6
?	?	?	?	?	16	100	290	W	2.1	1020.7	0	-1.3	?	?	?	?	?	?
?	?	?	?	?	16	?	?	?	0	1020.7	0	-0.3	19	?	?	?	0	1021

Appendix B. Stratus burn-off training data set.

smwT	smwRH	smwP	smwdP	sqlT	sqlTd	sqlWdd	sqlWdr	sqlWs	sqlTA	sqldT	sqldt	tamT	tamWdd	tamWdr	tamWs	tamTA	cond
?	?	?	?	?	?	?	?	?	?	?	?	8.2	341	N	5.1	-8.3	str
?	?	?	?	?	?	?	?	?	?	?	?	9.8	326	NW	3.1	-1.5	bo
?	?	?	?	?	?	?	?	?	?	?	?	9.2	347	N	2	1.8	str
?	?	?	?	?	?	?	?	?	?	?	?	10.1	?	?	1.5	?	bo
?	?	?	?	?	?	?	?	?	?	?	?	17.2	333	NW	3.1	23.2	str
?	?	?	?	?	?	?	?	?	?	?	?	18.7	316	NW	2.5	20.7	bo
?	?	?	?	?	?	?	?	?	?	?	?	15.5	333	NW	3.1	-1.9	str
?	?	?	?	?	?	?	?	?	?	?	?	16.1	344	N	3.6	3.7	bo
?	?	?	?	?	?	?	?	?	?	?	?	12	345	N	3.6	0.1	str
?	?	?	?	?	?	?	?	?	?	?	?	13	338	N	3.1	-0.1	bo
?	?	?	?	?	?	?	?	?	?	?	?	12.4	329	NW	4.1	?	str
?	?	?	?	?	?	?	?	?	?	?	?	13.3	320	NW	3.6	?	bo
?	?	?	?	?	?	?	?	?	?	?	?	10.9	67	NE	1	-9.7	str
?	?	?	?	?	?	?	?	?	?	?	?	12.2	217	SW	1.5	0.8	bo
?	?	?	?	?	?	?	?	?	?	?	?	17	319	NW	3.6	0.6	str
?	?	?	?	?	?	?	?	?	?	?	?	17.6	319	NW	3.1	6.4	bo
?	?	?	?	?	?	?	?	?	?	?	?	23.1	329	NW	2.5	11.1	str
?	?	?	?	?	?	?	?	?	?	?	?	24.9	317	NW	2.5	?	bo
?	?	?	?	?	?	?	?	?	?	?	?	24.6	306	NW	2	0	str
?	?	?	?	?	?	?	?	?	?	?	?	27.2	212	SW	1	-15.4	bo
?	?	?	?	?	?	?	?	?	?	?	?	23.2	177	S	3.6	5.3	str
?	?	?	?	?	?	?	?	?	?	?	?	23.8	177	S	3.6	-3.8	bo
?	?	?	?	?	?	?	?	?	?	?	?	21.5	182	S	2.5	-21.6	str
?	?	?	?	?	?	?	?	?	?	?	?	23	190	S	3.1	-31.1	bo
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	str
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	bo
17.8	?	?	?	?	?	?	?	?	?	?	?	23.2	306	NW	3.6	-3.6	str
18.3	?	?	?	?	?	?	?	?	?	?	?	22.4	338	N	5.1	24.5	bo
18.3	?	?	?	?	?	?	?	?	?	?	?	23.2	318	NW	4.6	11	str
18.3	?	?	?	?	?	?	?	?	?	?	?	23.9	320	NW	4.1	-2.4	bo
18.9	?	?	?	?	?	?	?	?	?	?	?	17.6	311	NW	4.6	18.8	str
19.4	?	?	?	?	?	?	?	?	?	?	?	19.7	304	NW	4.1	-8.6	bo
17.8	?	?	?	15	12.7	12	N	1.3	5	1.3	1.3	23.8	230	SW	2	-23	str
18.3	?	?	?	15.6	13.9	46	NE	1.6	0.2	1.9	2.3	25.4	207	SW	2	0	bo
18.9	?	?	?	17	13	260	W	3.1	3.1	2.1	4.3	22.9	303	NW	3.1	-1.2	str
19.4	?	?	?	16.8	13.8	35	NE	2.4	3.8	1.9	5.3	23.4	298	NW	2.5	-18.2	bo
18.3	?	?	?	16	13.7	11	N	2.4	6.7	2	7	25.3	324	NW	2.5	-22.8	str
18.9	?	?	?	16.6	14.2	?	?	3.8	?	2.6	8	27.2	323	NW	2	-59.6	bo
18.3	44	1012.5	1.8	15.3	13.8	112	E	2.8	7.4	?	?	26.2	346	N	3.6	4.5	str
18.9	48	1012.5	1.8	16.3	14.2	312	NW	1.5	2.6	?	?	27.1	344	N	3.6	-0.6	bo
18.3	41	1013.5	1.4	15.6	13.5	6	N	2.3	-1	1.8	4.6	26.4	199	S	1	-39.8	str
18.9	48	1013.9	1	18.2	14.5	80	E	2	11.2	4.4	5.6	28.3	230	SW	2	-61.6	bo
18.9	37	1015.2	1.8	17.3	13.5	19	N	2.7	0.1	3.7	8.5	23.7	133	SE	1.5	-20.9	str
18.9	47	1015.2	1.4	17.5	13.8	358	N	3.9	0.8	3.9	9.5	24.2	128	SE	2	-28.4	bo
17.8	39	1015.6	1.7	14.3	12.4	108	E	1.4	1.2	1.6	4.2	25.3	19	N	3.1	-7	str
18.3	47	1015.6	1.7	16.7	13.6	132	SE	1.9	5.1	4	5.5	26.6	20	N	2.5	16.2	bo
18.3	45	1014.2	1.8	14.4	14	143	SE	2.5	1	1.5	2.2	28.6	309	NW	1	0	str
18.3	50	1014.2	1.8	17.1	14.6	352	N	2.6	-1.7	4.2	3.2	29.5	356	N	1	-10.2	bo
18.3	33	1013.5	1.8	15.4	12.3	344	N	2.2	-0.7	1	3.3	19.4	333	NW	4.6	19.8	str
19.4	39	1013.9	1.4	16.3	13.2	?	?	1.6	?	1.9	4.3	20.5	330	NW	4.6	14	bo
17.8	28	1016.6	1.4	14.1	11.1	204	SW	1.9	-0.4	2.1	3.4	13.5	328	NW	2.5	2.1	str
18.3	36	1016.9	1.8	15.2	11.4	176	S	2.2	3.4	3.2	4.4	14.7	338	N	3.1	1.6	bo
16.7	41	1012.2	1.7	14.1	12.4	150	SE	3.3	?	1.2	3.7	22.9	348	N	2.5	?	str
18.3	42	1012.2	1.7	14.7	12.8	105	E	3.9	2.4	1.8	4.7	22.6	?	?	2.5	?	bo
17.8	35	1013.9	1.4	14.6	11.9	317	NW	1.5	1.6	2	4.6	25.6	204	SW	1	-46.7	str
18.3	43	1013.9	1.7	15.5	12.7	?	?	2.4	?	2.9	5.6	26.7	198	S	1	-53.8	bo
20	27	1013.2	1.7	16.3	12.4	241	SW	3.2	-1.9	2.1	10.4	18.1	298	NW	1.5	-2	str
20	42	1013.2	1.7	17.6	12.4	306	NW	3	-1.1	3.4	11.4	17.3	169	S	1	1.6	bo
21.7	20	1010.5	1.7	18.1	12.7	251	W	4.2	0	4.2	6.5	10.9	219	SW	2	6.3	str
22.2	30	1010.8	1.4	18.3	12.1	287	W	6.7	3.1	4.4	7.5	11	247	SW	2	6.4	bo
19.4	32	1012.2	1.4	14.1	11.8	137	SE	2.1	-4.6	1	1.3	9.9	327	NW	6.1	-17.8	str
20	41	1012.2	1.4	15.8	12.9	132	SE	2.6	-1.1	2.7	2.3	10.7	320	NW	5.6	-17.7	bo
17.8	29	1009.8	1.7	14.4	11.3	245	SW	2.7	[illegible]	0.8	1.5	18.8	158	S	2	6.6	str
18.3	37	1010.2	1.3	14.8	11.4	281	W	2	0	1.2	2.5	20.2	148	SE	2.5	-12.9	bo
19.4	25	1012.2	1.7	16.3	11.8	275	W	4.2	?	2.3	6.4	18.5	199	S	2.5	-6.2	str
20	37	1012.2	1.7	17.3	12.3	328	NW	4.5	-1.8	3.3	7.3	20.1	212	SW	2	6.3	bo
20.6	19	1013.2	1.7	18.2	11.7	228	SW	4.4	?	4.9	8.2	10.8	296	NW	3.1	?	str
21.1	35	1012.9	1.7	19.5	11.9	261	W	4	-2.3	6.2	9.2	10.6	304	NW	3.1	8.8	bo
19.4	36	1009.5	1.4	16.5	13.4	266	W	5.4	0.4	1	1	10.1	319	NW	6.1	-12.9	str
21.1	37	1009.5	1.4	17.9	12.8	290	W	6	4.8	2.4	1.9	10.4	322	NW	6.1	-10.3	bo
22.8	31	1010.8	1.8	19.9	15.7	255	W	6.8	-0.8	3.4	15.3	13.5	300	NW	3.6	1	str
22.8	39	1010.8	1.8	19.7	15	246	SW	5.4	-6.6	3.2	16.3	14.6	303	NW	4.6	11.5	bo
17.2	30	1013.9	1.4	13.5	10.7	280	W	3.9	1.9	0.8	5.3	20.1	111	E	1	4.6	str
17.8	39	1014.2	1.4	14.4	11.3	306	NW	3.2	5.1	1.7	6.3	20.3	127	SE	1	0	bo
16.1	20	1014.6	1.4	12.5	8.7	259	W	4.5	-0.2	0.3	0.7	14.7	325	NW	3.1	0.9	str
17.2	36	1015.2	1.4	14	9.3	252	W	3.1	0	1.8	1.7	15.6	333	NW	3.1	-0.3	bo
18.3	35	1013.5	1.8	14.7	12.3	8	N	1.8	0.5	2.6	8.8	22.4	105	E	1.5	-14.1	str
18.9	46	1013.5	1.8	16.8	13	14	N	3.1	-0.1	4.7	9.8	23.7	119	SE	1.5	-24.6	bo
18.3	33	1013.9	1.4	14.6	12.1	56	NE	2.9	?	2.2	8	20.2	5	N	4.1	?	str
18.9	41	1013.5	1.8	16	12.3	60	NE	2.8	0	3.6	8.9	21.7	40	NE	3.1	3.1	bo
18.3	34	1015.9	1.7	15.1	12.4	354	N	2.1	-0.2	2.1	9.2	21.7	355	N	5.1	28.3	str
18.9	44	1015.9	1.7	16.7	12.8	347	N	2.8	0.4	3.7	10.2	22.1	352	N	4.6	13.1	bo
17.2	35	1018.3	1.7	13.4	11.5	357	N	1.9	0.4	0.7	6.9	24	123	SE	3.1	-56.9	str
17.2	43	1018.3	1.7	14.9	12.3	32	NE	1.9	?	2.2	7.8	24.8	136	SE	2.5	?	bo
17.8	38	1013.5	1.8	13.8	12.2	25	NE	1.7	-1.3	2.1	5.9	25.4	169	S	1.5	-0.2	str
18.3	44	1013.5	1.4	14.9	12.7	355	N	2.7	-5	3.2	6.9	25.6	170	S	2	-55.8	bo
19.4	28	1010.4	1.5	16.6	12	342	N	6	-1.1	3.9	7.5	15.2	115	SE	1.5	5.8	str
20	39	1009.5	2	17.5	12.2	270	W	5.4	-1.1	4.8	8.2	15.8	97	E	1	1.1	bo
21.7	20	1012.4	1.5	20	13	270	W	5.1	-11.9	5.1	9.6	12.6	193	S	2.5	-7.5	str
22.8	28	1011.9	1.7	18.5	12.7	271	W	6.9	-1.5	3.6	10.6	13.9	190	S	2.5	12.9	bo
18.9	31	1015.9	1.7	15.4	12.1	2	N	2.7	0.3	1.6	6.5	20.7	175	S	1	-12.9	str
18.9	44	1015.9	1.7	16.6	12.7	12	N	2.9	1.4	2.8	7.5	19.5	212	SW	1	-12.3	bo
17.8	33	1015.9	1.7	13.1	11.5	319	NW	2.8	?	0.6	7.7	18.9	16	N	3.1	?	str
17.8	42	1015.9	1.4	14.5	11.9	17	N	2.3	-0.7	2	8.7	21.8	79	E	1.5	-3.7	bo
13.9	52	1018	0.3	13.5	10.3	272	W	5.1	-1.2	2	2.9	23	350	N	1	-27.2	str
14.4	60	1017.6	0.4	14.7	10.7	334	NW	4.5	-1.3	3.2	3.9	23	109	E	1.5	-41.7	bo
13.9	52	1016.9	0.1	13.4	10.6	342	N	2.9	-3.6	1.6	2.2	22.1	296	NW	1.5	17.8	str
14.4	60	1016.9	0.1	14.7	11.1	311	NW	2.3	-0.2	2.9	3.2	23.3	310	NW	1.5	-5	bo
13.9	55	1014.9	0.4	13.3	11.4	159	S	2.9	6.8	1.1	2.5	19.8	321	NW	5.6	25.4	str
14.4	62	1014.9	0.4	13.9	11.7	90	E	1.7	7.2	1.7	3.5	21	323	NW	4.6	19.5	bo
17.2	68	1015.6	0	17	15	149	SE	2.1	0	1.2	1.3	15.4	317	NW	3.6	-2.6	str
17.8	67	1015.6	0	17.7	15	181	S	2.6	3.7	1.9	2.3	17.4	309	NW	3.1	-0.2	bo
17.8	60	1016.9	0.1	17	15.5	65	NE	2.3	0	2.8	2.8	13.8	336	NW	2.5	-5.3	str
19.4	56	1016.9	0.1	17.9	15.8	73	E	3.1	-0.3	3.7	3.8	13.5	344	N	1	6	bo
17.8	64	1020.7	0	17.6	15.3	327	NW	2	3.1	1	-1.4	12.6	326	NW	3.6	-6.1	str
17.8	62	1020.3	0.4	16.7	14.8	66	NE	1.5	0.4	0.1	-0.4	12.9	325	NW	3.6	-11.1	bo

Appendix B. Stratus burn-off training data set.

Year	JulDate	TimeZ	VVVeta	LIeta	VVVngm	LIngm	sfoInHt	sfoInSt	sqlInHt	sqlInSt	sfoCld%	sfoCldBs	sqlCld%	sqlCldBs	SolAng	sfoRad	sqlRad	funT
1997	151	12.6	7	3	4	3	1475	3.6	?	?	0.38	152	?	?	7.4	0	2	16.5
1997	151	13.6	7	3	4	3	1600	2.2	?	?	0.19	152	0.75	457	18.7	50	48	16.7
1997	159	14.25	9	4	33	5	1250	1.8	?	?	?	?	0.19	457	28	163	159	11.8
1997	159	15.25	9	4	33	5	1750	3.6	?	?	0.38	579	0.38	457	39.9	351	375	12
1997	168	14.3	7	9	9	7	1600	3.6	?	?	0.38	274	0.19	274	28.3	200	204	11.1
1997	168	15.3	7	9	9	7	2675	1.9	?	?	0.38	274	0.38	335	40.2	216	392	11
1997	179	17.63	?	?	?	?	525	4	?	?	0.75	426	0.38	457	68.4	781	787	12.8
1997	179	18.63	?	?	?	?	525	5.7	?	?	0.75	426	0.75	457	75.3	793	563	13.4
1997	185	16	-5	8	-11	5	1775	4.1	?	?	0.19	243	0.19	243	48.8	140	522	13
1997	185	17	-5	8	-11	5	1600	3	?	?	0.19	243	0.19	243	60.3	418	702	13.1
1997	186	16.33	-12	11	-11	10	1400	3	?	?	0.75	182	0.38	274	51.7	587	604	12.4
1997	186	17.33	-12	11	-11	10	1450	2.6	?	?	1	182	0.38	365	63	355	743	12.7
1997	194	14.88	14	10	-8	8	1775	2.2	?	?	1	365	1	335	36.4	129	117	12.6
1997	194	15.88	14	10	-8	8	750	3.7	?	?	0.75	365	1	457	48.3	459	334	13
1997	195	14.92	26	9	21	8	1650	2.6	?	?	1	365	1	304	36.3	149	142	12.6
1997	195	15.92	26	9	21	8	1575	4	?	?	0.75	335	?	?	48.2	387	332	12.7
1997	196	14.83	-7	9	-19	9	1450	3.4	?	?	0.75	335	1	396	33.3	178	193	11.6
1997	196	15.83	-7	9	-19	9	1350	2.8	?	?	0.75	335	0.75	426	48.1	525	439	11.6
1997	199	14.32	0	10	-1	8	525	1.7	?	?	1	274	0.19	304	27.1	66	177	11.8
1997	199	15.32	0	10	-1	8	1675	3.2	?	?	0.75	213	0.38	304	39	143	346	11.7
1997	200	14	23	6	-6	5	775	3	300	11	0.38	396	0.38	213	24	28	46	12.8
1997	200	15	23	6	-6	5	1275	3	300	8.3	0.38	304	0.38	213	35.9	285	288	12.8
1997	201	15.85	-3	9	5	8	1925	3.2	300	14.5	1	426	1	365	44.7	451	268	12.6
1997	201	16.85	-3	9	5	8	1800	3.2	350	7.1	1	426	0.75	396	56.2	436	687	12.8
1997	202	14.75	3	6	-2	6	1550	3	400	6.1	1	365	?	?	32.7	278	265	12.5
1997	202	15.75	3	6	-2	6	1625	3.3	300	10	1	365	0.75	365	44.6	427	237	12.5
1997	207	15.22	23	8	-14	5	1525	3	250	21.2	0.38	274	1	274	38.1	293	371	12.3
1997	207	16.22	23	8	-14	5	575	4.1	275	12.6	?	?	1	274	49.8	522	222	12.4
1997	208	14.95	-10	9	-7	10	2300	1.9	275	17.7	0.38	609	1	487	35	114	105	14.3
1997	208	15.95	-10	9	-7	10	2350	3.1	325	8.6	0.38	731	0.75	487	46.8	449	326	14.9
1997	209	15.4	19	6	-14	3	1625	3.6	300	8.7	1	396	1	426	40.8	147	214	12.4
1997	209	16.4	19	6	-14	3	1225	2.8	275	10.7	0.38	426	?	?	52.4	356	434	12.8
1997	210	15.33	-7	3	31	3	2125	3.8	300	12.8	0.75	457	1	487	37.7	86	705	14.3
1997	210	16.33	-7	3	31	3	2075	4	300	9.4	0.75	457	0.75	487	49.4	222	315	14.4
1997	211	15.33	9	4	19	4	1375	2.5	425	7.5	0.75	396	?	?	37.6	146	274	13.3
1997	211	16.33	9	4	19	4	1950	2.7	325	7.2	0.75	396	0.75	609	49.3	183	602	13.1
1997	212	15.37	-4	8	-1	6	1775	2.7	250	15.5	1	304	0.75	304	37.4	210	211	13.2
1997	212	16.37	-4	8	-1	6	825	2.7	350	7.5	0.75	304	0.38	457	49.1	286	550	13.4
1997	218	14.5	-3	11	-6	9	1350	5	225	26.1	0.19	213	0.75	243	27.6	97	102	12.7
1997	218	15.5	-3	11	-6	9	1050	4.7	325	9.7	0.19	213	1	7620	39.5	335	203	12.6
1997	220	14.77	14	6	1	3	1800	4.2	400	9.1	0.75	365	1	304	30.3	243	247	14.2
1997	220	15.77	14	6	1	3	1825	4.1	250	11.3	0.38	365	1	365	42	348	154	14.7
1997	221	14.75	23	4	2	10	1250	2	375	6.9	0.75	822	0.38	762	30.1	32	26	15.4
1997	221	15.75	23	4	2	10	525	2.5	300	7.9	0.75	822	?	?	41.9	255	201	16.1
1997	223	15.33	15	8	-22	5	600	4	325	6.9	0.19	396	1	762	35.7	80	146	14.9
1997	223	16.33	15	8	-22	5	450	6.4	275	20.9	0.19	396	0.75	762	47.2	583	354	15.3
1997	224	15.87	?	?	2	6	1150	3	400	6.8	1	335	?	?	41.3	169	180	13.5
1997	224	16.87	?	?	2	6	1175	3.5	450	5.7	1	335	?	?	52.4	519	283	13.6
1997	225	15.75	-4	9	-9	6	1650	9.2	275	7.9	1	335	?	?	41.1	133	133	14.6
1997	225	16.75	-4	9	-9	6	1575	3.7	275	8	0.75	396	?	?	52.2	562	481	15
1997	226	17	2	9	10	9	1475	2.7	325	9	0.38	274	0.75	335	54.5	590	707	13.1
1997	226	18	2	9	10	9	1150	3.5	250	11.6	0.19	274	?	?	63	777	787	13.3
1997	227	14.75	12	8	-11	9	1900	6.8	275	9.5	0.75	335	1	426	29	78	187	13.9
1997	227	15.75	12	8	-11	9	375	4.7	400	7.2	0.75	396	?	?	40.7	254	183	14
1997	228	15.83	7	9	-8	10	1525	1.7	275	11.4	1	548	0.38	457	40.5	198	489	14.9
1997	228	16.83	7	9	-8	10	700	2.7	250	12.2	0.75	548	0.38	457	51.5	503	666	15.3
1997	229	17.17	-4	11	3	11	575	4.4	250	16.1	0.19	853	0.75	853	56.2	431	354	17.1
1997	229	18.17	-4	11	3	11	3075	1.7	300	9.3	0.75	1036	0.75	914	63.6	880	812	17.8
1997	235	17.4	4	7	16	5	925	1.9	275	11.6	1	365	?	?	56.7	844	759	17.3
1997	235	18.4	4	7	16	5	575	4.3	525	6.2	1	487	0.38	396	62.7	329	360	18.1
1997	236	14.13	17	7	?	?	725	3.2	300	9.4	0.19	365	0.75	518	21.3	37	29	17.3
1997	236	15.13	17	7	?	?	675	3	275	13.5	0.38	365	?	?	33	208	177	17.5
1997	237	14.8	5	9	11	10	725	3.3	225	23.7	0.38	487	?	?	27	159	160	17.4
1997	237	15.8	5	9	11	10	450	5.7	275	5.1	0.75	670	?	?	38.5	373	385	17.6
1997	238	14.5	36	4	26	3	675	3.3	225	33.1	?	?	0.38	426	23.8	115	113	17.5
1997	238	15.5	36	4	26	3	575	2.3	300	11.7	0.75	487	0.75	609	35.5	319	314	17.7
1997	241	17.42	5	9	-15	9	575	3.8	325	9.8	1	365	0.19	304	54.8	683	684	17.5
1997	241	18.42	5	9	-15	9	550	3.9	300	10.1	1	426	0.19	304	60.5	235	621	17.8
1997	242	15.57	20	9	-2	9	1125	2.5	275	10.8	0.75	457	0.38	457	34.5	121	330	16.3
1997	242	16.57	20	9	-2	9	700	3.9	225	9.7	1	426	0.19	304	45.4	353	537	16.6
1997	245	15.5	28	2	24	3	1900	2.3	350	6.4	1	396	0.19	304	33.8	253	206	16.6
1997	245	16.5	28	2	24	3	900	2.7	225	25.2	1	396	0.19	304	44.5	167	521	17.2
1997	246	14.5	6	4	-21	5	850	3.9	325	7	0.75	518	0.38	487	22	81	84	17
1997	246	15.5	6	4	-21	5	625	3.6	250	15.9	0.75	548	0.19	487	33.5	253	206	17.5
1997	250	15.7	-7	10	-7	7	1725	4.1	300	6.8	1	335	0.38	426	35.3	434	382	15.1
1997	250	16.7	-7	10	-7	7	1450	4.6	250	19.6	1	335	0.38	426	45.5	261	573	15.3
1997	254	15.87	18	6	-7	6	1050	3.5	250	12.6	0.19	365	0.75	457	34.2	306	357	16.8
1997	254	16.87	18	6	-7	6	925	2.1	325	9.1	0.19	365	0.75	457	44.3	560	577	16.9
1997	255	13.92	8	7	12	6	2875	1.9	250	2.7	0.38	426	0.38	457	13.9	3	5	15.4
1997	255	14.92	8	7	12	6	1550	2.7	325	11.3	0.75	426	0.38	365	25.5	124	147	15.6
1997	256	15.58	23	6	-1	7	2350	2.1	225	9.9	1	640	?	?	30.9	286	?	16.1
1997	256	16.58	23	6	-1	7	500	2.8	275	9.8	1	701	0.75	487	41.3	385	538	16.5
1997	258	14.5	-29	9	5	8	3575	2.1	?	?	0.19	304	0.75	457	19	58	?	13.9
1997	258	15.5	-29	9	5	8	1300	1.8	?	?	0.19	487	1	457	30.3	110	?	15.6
1997	265	15.58	10	8	-12	7	1625	4.5	275	7.9	1	274	1	335	28.4	248	259	14.1
1997	265	16.58	10	8	-12	7	1675	4.2	350	4.9	0.75	335	0.75	518	38.5	362	252	14.5
1997	269	16.5	3	10	?	7	950	3.3	375	6	0.38	274	?	?	16.2	?	?	16.4
1997	269	17.5	3	10	?	7	700	3.6	275	12.7	0.19	274	?	?	27.3	218	275	16.8
1997	273	15.5	26	8	18	8	1575	2	1625	5.4	0.38	396	?	?	26.1	124	193	14.7
1997	273	16.5	26	8	18	8	1650	3.5	275	8.3	0.75	365	1	396	35.9	160	358	15.3
1997	274	16.58	16	9	32	9	2725	2	275	7.9	0.19	548	0.38	548	35.6	332	440	16.2
1997	274	17.58	16	9	32	9	2125	2.3	325	7.8	0.19	548	0.38	548	43.3	180	582	16.5
1997	275	15.75	-23	11	-28	12	1100	5.3	300	7.3	0.19	457	0.38	304	28.1	252	262	15.6
1997	275	16.75	-23	11	-28	12	350	2	325	9.5	?	?	0.75	457	37.4	315	316	16.3
1997	282	14.75	6	5	21	5	1600	1.9	225	16.3	0.75	762	?	?	15.6	9	13	13.1
1997	282	15.75	6	5	21	5	1500	1.8	325	8.4	0.38	518	0.38	304	26.1	89	104	13.7
1997	294	16.8	-32	8	-20	8	1400	5.7	425	4.6	1	274	1	365	31.4	90	157	12.2
1997	294	17.8	-32	8	-20	8	1250	4.9	275	9.9	0.75	274	?	?	37.6	438	516	12.4
1997	295	17.58	-8	10	6	10	1700	8.1	525	4.6	1	335	1	487	36	464	500	12.5
1997	295	18.58	-8	10	6	10	450	4.7	275	9.5	1	335	0.75	487	39.8	372	380	12.7

Appendix B. Stratus burn-off training data set.

fsnTd	fsnWdd	fsnWdr	fsnWs	fsnTA	fsndT	fsndc	hwdT	hwdRH	hwdWdd	hwdWdr	hwdWs	hwdP	hwddP	hwdTA	anqT	anqRH	anqWdd	anqWdr
16.5	188	S	1	5.2	1.5	8.9	?	?	?	?	?	?	?	?	19	83	190	S
16.7	90	E	1	0	1.7	9.8	19	88	180	S	2.6	1018	-0.7	0	19	83	180	S
11.1	193	S	4.1	6.5	0.6	6.8	14	82	270	W	4.1	1008.5	0	0	14	77	130	SE
11.2	193	S	5.6	?	0.8	7.8	15	77	200	S	5.1	1009.2	-0.4	?	16	67	140	SE
11.1	253	W	4.6	1.7	0.2	-0.7	14	94	300	NW	4.1	1015.3	-0.7	0.7	16	77	?	?
11	255	W	5.1	2.8	0.1	0.3	15	88	300	NW	4.1	1015.6	-0.7	4.9	16	82	330	NW
12	252	W	6.1	7.9	0.9	4.1	16	77	290	W	5.1	1018.3	-0.7	0	19	52	300	NW
12.3	258	W	6.1	4	1.5	5.3	18	72	320	NW	6.7	1018.3	0	5.7	19	52	260	W
13	228	SW	5.1	-1.7	0.3	2.5	16	94	250	W	2.6	1014.6	-0.3	-0.2	17	77	?	?
13.1	237	SW	6.1	1.3	0.4	3.5	17	82	300	NW	3.1	1014.6	-0.3	0	19	68	?	?
12.4	254	W	5.6	-1.2	0.3	1.8	15	88	290	W	4.1	1017.6	0	2.7	17	77	360	N
12.7	248	W	5.6	-0.1	0.6	2.8	16	88	270	W	5.1	1018	-0.4	0	19	73	360	N
12.6	198	S	6.1	6.4	0.1	0.9	16	88	?	?	0	1015.6	-0.7	0	18	77	40	NE
13	202	S	5.6	-6.6	0.5	2	18	77	?	?	0	1016	-0.7	-1.6	18	77	?	?
12.5	196	S	4.6	1	0.2	3.4	15	88	340	N	4.1	1017	-0.7	-0.5	17	82	10	N
12.6	208	SW	4.6	9	0.3	4.5	?	?	?	?	?	?	?	?	18	77	?	?
11.6	226	SW	3.6	8.4	0	-0.9	16	88	?	?	0	1018	-0.4	2.4	17	82	?	?
11.6	229	SW	3.6	5.4	0	0	18	77	?	?	0	1018.3	-0.3	2.2	19	73	340	N
11.8	241	SW	4.1	1	0.1	-1.2	14	94	250	W	3.6	1014.6	-0.3	1	16	82	150	SE
11.7	217	SW	3.1	0.5	0	-0.3	15	88	300	NW	2.6	1014.6	0	0.7	17	77	130	SE
12.3	214	SW	5.6	3.6	0	-1	14	88	330	NW	3.1	1011.9	-0.4	0	17	82	350	N
12.5	199	S	6.6	16	0	0	16	82	340	N	2.6	1012.2	-0.3	0	18	72	?	?
12.6	220	SW	4.1	6.1	0.2	0.4	16	88	290	W	3.6	1014.9	-0.6	1	18	72	130	SE
12.7	219	SW	4.6	12.9	0.4	1.3	17	82	290	W	3.6	1014.9	-0.6	0	18	72	100	E
12.5	204	SW	5.1	0.4	0.1	-0.8	16	88	290	W	2.6	1014.9	-0.3	-2	17	77	?	?
12.5	200	S	5.6	5.4	0.1	0.3	16	88	260	W	2.6	1013.2	1.4	0	18	72	80	E
12.3	202	S	6.6	?	0.3	2.2	15	94	290	W	2.6	1012.9	-0.3	?	17	82	360	N
12.4	203	SW	6.6	7.4	0.4	3.3	15	94	?	?	0	1013.6	-0.7	1	19	73	360	N
13	202	S	6.6	-0.4	0.4	0.9	17	82	300	NW	2.6	1014.3	-0.7	-5	17	77	100	E
13.1	200	S	6.1	-4.5	1	2	17	82	?	?	0	1014.6	-0.7	0	18	68	?	?
11.8	217	SW	4.1	2.9	0.1	1.4	15	88	200	S	2.6	1013.9	0	-1.8	18	72	?	?
12	232	SW	4.6	11.6	0.5	2.5	17	77	270	W	2.6	1014.6	-1	1.9	20	68	350	N
13.5	199	S	4.6	-0.8	0.6	2.6	17	77	270	W	2.6	1015.6	-0.3	-2.1	17	72	130	SE
13.7	213	SW	4.1	7.1	0.7	3.5	20	68	290	W	4.1	1016	-0.7	-6.7	21	60	?	?
13	229	SW	5.6	-2.9	0.3	-0.4	16	88	150	SE	4.6	1018	-0.4	4.2	18	68	130	SE
12.9	222	SW	5.6	-0.5	0.1	0.5	18	77	280	W	5.1	1018.7	-0.7	-1	21	60	?	?
12.9	247	SW	5.1	-1	0.1	0.4	16	88	270	W	0	1019.3	0	4.8	17	72	90	E
12.9	242	SW	3.6	1.9	0.3	1.3	17	82	300	NW	4.1	1020	-0.3	0.8	19	68	360	N
12.7	204	SW	5.1	8.8	0.2	-0.8	16	94	?	?	0	1014.9	-0.3	2.9	18	85	?	?
12.6	198	S	5.1	5.4	0.1	0.3	18	83	?	?	0	1015.3	-0.4	0	19	83	?	?
14.2	197	S	6.6	3.9	0.7	1	?	?	?	?	3.6	1011.5	-0.3	?	19	83	360	N
14.6	205	SW	7.1	-0.3	1.2	2	18	83	31w	NW	3.6	1011.9	-0.7	0	19	83	?	?
14.5	173	S	4.6	-3.4	0.9	5.5	18	77	310	NW	0	1010.9	-0.7	0	19	68	150	SE
14.6	181	S	3.6	-10.1	1.6	6.5	?	?	?	?	?	?	?	?	?	?	?	?
14.6	240	SW	2	?	0.7	1.3	17	82	?	?	0	1016.3	-0.3	?	19	73	360	N
14.6	259	W	2.5	-3.1	1.1	2.3	20	68	270	W	2.6	1016.6	-0.3	-0.6	20	64	?	?
13.4	207	SW	1.5	7.9	0.2	1.4	?	?	?	?	?	?	?	?	?	?	?	?
13.5	224	SW	3.1	12.6	0.3	2.3	?	?	?	?	?	?	?	?	?	?	?	?
13.9	185	S	2	?	0.8	10	?	?	?	?	?	?	?	?	?	?	?	?
14	214	SW	3.1	-5.9	1.2	11	?	?	?	?	?	?	?	?	?	?	?	?
13.1	212	SW	2.5	14.7	0.4	3	18	77	280	W	2.6	1016.3	-0.7	-0.1	19	77	10	N
13.3	235	SW	3.6	9	0.6	4	?	?	?	?	?	?	?	?	?	?	?	?
13.5	247	SW	3.6	-3.1	0.4	4.3	16	82	260	W	2.6	1013.9	-0.3	-0.9	18	77	?	?
13.7	227	SW	3.6	1.6	0.5	5.3	?	?	?	?	?	?	?	?	19	73	?	?
14.6	223	SW	6.6	-8.1	0.1	0.6	19	73	200	S	4.1	1013.9	-0.3	-0.7	19	68	?	?
14.3	221	SW	6.6	-13	0.5	1.5	20	68	220	SW	4.6	1014.3	-0.4	-8.9	21	60	?	?
15.8	201	S	5.6	3.5	1.6	7.2	19	73	260	W	3.1	1017.6	-0.6	0	21	60	240	SW
16	204	SW	5.6	11.1	2.3	8.3	20	68	260	W	3.1	1018	-0.7	-0.9	22	53	350	N
17	252	W	2.5	-2.1	0.9	1.7	?	?	?	?	?	?	?	?	?	?	?	?
17.1	213	SW	2	4.8	1.7	2.8	20	83	260	W	3.1	1019.3	-0.6	0	22	69	20	N
17.3	232	SW	1.5	1.3	0.4	-0.4	19	88	?	?	0	1019.3	-0.3	2.5	19	77	280	W
16.7	267	W	2.5	1.9	0.6	0.5	?	?	?	?	?	?	?	?	?	?	?	?
16.5	284	W	4.1	-0.3	0.4	1.1	?	?	?	?	?	?	?	?	?	?	?	?
16.5	273	W	3.1	2.8	0.6	2	?	?	?	?	?	?	?	?	21	64	290	W
17.5	239	SW	2	3	0.6	1.5	19	88	270	W	2.6	1016.3	-0.3	0	19	73	190	S
17.7	224	SW	2.5	4.3	0.8	2.5	20	83	270	W	2.6	1017	-0.4	1.3	22	69	40	NE
16.1	276	W	5.1	-1.3	0.9	3.2	20	78	280	W	6.2	1016	-0.4	-3.1	22	64	350	N
16.4	262	W	4.1	-1.9	1.2	4.3	20	78	260	W	4.1	1016	0	0.8	24	57	360	N
15.4	273	W	5.1	-0.8	0.2	0.6	18	83	260	W	4.6	1014.6	-0.7	1	19	73	40	NE
15.5	268	W	4.6	1	0.5	1.5	19	77	260	W	5.1	1014.6	-0.7	1.1	21	64	10	N
16	256	W	3.6	-2.2	0.4	4.5	19	83	250	W	2.6	1016.3	-0.3	0.1	19	64	170	S
16.3	234	SW	3.6	-0.2	1	5.5	19	83	?	?	0	1017.3	-0.7	0	22	60	?	?
16.3	267	W	1.5	1.3	0.2	0.3	19	83	?	?	0	1019.7	-0.7	3.1	18	72	?	?
16.1	220	SW	2	2.9	0.7	1.3	19	77	?	?	0	1020	-1	0	21	64	20	N
14.3	289	W	5.1	-2.9	0.4	0.9	17	82	280	W	5.1	1017	-0.4	0.9	19	64	?	?
14.4	276	W	5.1	-0.5	0.6	2	18	83	260	W	3.6	1017	0	1.4	20	60	50	NE
16.3	287	W	3.6	-0.7	0.3	1.9	19	83	260	W	4.1	1013.6	-0.7	0.9	22	60	?	?
16.4	253	W	2	3.5	0.4	3	19	83	260	W	4.1	1013.6	-0.7	-1.2	23	57	330	NW
15	243	SW	17	-9.6	0	-0.3	17	88	260	W	2.6	1009.9	-0.7	0	18	72	?	?
15	274	W	4.1	-0.9	0.2	0.8	17	88	?	?	0	1010.2	-0.7	0	19	73	?	?
15.2	250	W	18	-15.2	0.2	1.8	18	77	280	W	2.6	1011.5	-0.6	0	19	64	60	NE
15.4	249	W	4.1	-0.2	0.6	2.8	19	73	240	SW	4.1	1011.9	-0.7	0.9	20	60	?	?
13.7	118	SE	15	14.1	0.6	1.8	15	88	?	?	0	1020.7	-0.3	0	17	72	150	SE
14.8	96	E	2	-0.3	2.3	2.8	18	77	260	W	2.6	1021	-0.3	-7.9	19	68	?	?
13.3	293	NW	16	-11.3	0.2	1.6	16	88	?	?	0	1013.6	-0.7	2.7	18	72	30	NE
13.6	268	W	2.5	0.6	0.6	2.5	17	82	?	?	0	1013.6	-0.7	2.5	19	68	360	N
16.1	271	W	?	?	0.9	5	?	?	?	?	?	?	?	?	21	68	340	N
16.3	285	W	4.1	1.7	1.3	6	19	83	280	W	3.6	1021.7	-0.7	0	21	73	360	N
13.7	195	S	16	1.7	0.8	3	16	88	?	?	0	1014.9	0	1.3	18	88	?	?
13.7	240	SW	3.1	?	1.4	4	19	73	270	W	3.1	1015.3	0	?	20	68	10	N
15.3	199	S	19	5.1	0.8	10.8	19	77	270	W	4.1	1013.6	-0.4	-2	21	64	?	?
15.4	199	S	5.1	-0.8	1.1	11.8	20	73	270	W	4.1	1013.6	0	-5.1	22	60	10	N
15.3	86	E	17	21.1	1.9	3.5	17	88	?	?	0	1016.6	-0.6	0	18	72	280	W
15.4	243	SW	1.5	-1.2	2.6	4.5	18	77	?	?	0	1017	-0.7	0	19	73	270	W
13	149	SE	?	?	0.2	3.8	?	?	?	?	?	?	?	?	?	?	?	?
13.4	171	S	1.5	-0.3	0.8	4.8	14	94	190	S	2.6	1015.6	-0.3	0	16	82	120	SE
11.8	249	W	15	-7.7	0.3	1.3	15	82	?	?	0	1020.7	-0.7	-0.1	17	68	?	?
11.9	198	S	1.5	?	0.5	2.3	?	?	?	?	?	?	?	?	17	68	?	?
12.2	280	W	3.1	0.5	0	0.1	14	88	?	?	0	1019.7	-0.7	4.5	16	72	?	?
12.3	243	SW	2.5	1.9	0.2	1	15	82	?	?	0	1019	0	1.7	17	68	?	?

Appendix B. Stratus burn-off training data set.

nuqWs	nuqP	nuqdP	nuqTA	nuqdT	nuqdt	oakT	oakRH	oakWdd	oakWdr	oakWs	oakP	paoT	paoRH	paoWdd	paoWdr	paoWs	paoP	rbvT
1.5	1018	-0.7	0	0	-1.32	19	77	?	?	0	1013	?	?	?	?	?	?	?
2.1	1018	-0.7	0	0	-0.32	21	73	?	?	1.5	1018	19	83	?	?	3.1	1017.3	19
8.2	1008.2	0.3	0	1	3.33	16	72	190	S	3.1	1008.5	15	77	150	SE	6.7	1008.5	14
5.7	1008.8	0	?	3	4.33	16	72	140	SE	2.1	1009.2	16	67	150	SE	3.6	1009.2	16
0	1014.6	0	11.2	1	1.38	14	82	200	S	4.1	1014.9	14	94	80	E	3.1	1014.9	15
2.6	1014.9	0	7.2	1	2.38	14	82	230	SW	5.1	1015.3	15	88	10	N	2.6	1014.9	16
6.2	1018.3	-0.7	0.2	6	4.71	18	68	240	SW	10.3	1018.3	18	59	280	W	5.1	1017.6	17
6.2	1018.7	-0.4	2	6	5.71	18	68	270	W	7.7	1018.7	19	56	280	W	5.1	1018	19
1.5	1014.3	0	?	1	1.08	16	77	210	SW	3.6	1014.6	17	77	260	W	2.6	1014.3	17
2.1	1014.3	0	?	3	2.08	16	77	220	SW	5.1	1015.3	19	73	10	N	2.6	1014.3	18
2.6	1017.3	0.3	4.4	1	2.41	16	77	230	SW	5.1	1017.6	17	77	?	?	1.5	1017.3	18
3.6	1017.6	0	3.4	3	3.41	?	?	?	?	?	?	19	77	10	N	5.1	1018	?
1.5	1014.9	0	0.3	2	4.96	17	72	360	N	2.6	1015.3	17	82	?	?	1.5	1014.9	17
0	1015.3	0	-3	2	5.96	17	72	350	N	2.6	1015.6	19	77	?	?	1.5	1014.9	19
2.1	1016.3	0	-5.1	1	2	16	72	330	NW	2.6	1017	16	88	20	N	3.1	1016.3	17
0	1016.6	0	4.2	2	3	?	?	?	?	?	?	?	?	?	?	?	?	?
0	1017.6	0	6.2	1	4.91	17	72	320	NW	2.6	1018	17	82	?	?	1.5	1017.6	17
1.5	1018	0	2.4	3	5.91	17	72	300	NW	5.1	1018.3	17	82	?	?	1.5	1016	19
3.1	1014.3	-2.8	16.5	1	2.4	15	77	260	W	4.1	1014.6	13	88	?	?	0	1014.6	14
2.6	1014.6	0	8.9	2	3.4	16	77	240	SW	4.1	1014.9	16	82	160	S	3.6	1014.6	16
2.1	1011.5	2.8	4.1	1	1.08	16	77	340	N	3.1	1011.9	15	88	320	NW	1.5	1011.5	15
1.5	1011.9	0	?	2	2.08	17	68	350	N	2.6	1012.6	17	82	350	N	1.5	1011.9	15
2.6	1014.6	0	16.6	1	0.93	?	?	?	?	?	?	17	82	40	NE	3.6	1014.6	15
3.1	1014.3	0	6.2	1	1.93	17	72	270	W	5.1	1014.9	18	77	80	E	3.6	1014.6	18
1.5	1014.6	-2	?	0	-0.17	17	72	20	N	3.6	1014.9	17	88	?	?	1.5	1014.6	15
2.1	1014.9	-0.3	3	1	0.83	17	72	300	NW	2.6	1015.3	17	82	?	?	1.5	1013.6	17
2.1	1012.2	1.4	?	0	0.3	15	82	330	NW	4.1	1012.9	16	88	10	N	3.6	1012.2	17
2.6	1012.9	0	-2.8	2	1.3	16	77	250	W	2.6	1013.2	17	82	360	N	2.1	1012.9	18
2.1	1013.6	0.3	-0.4	2	3.03	17	72	240	SW	4.1	1014.3	16	82	70	E	4.1	1013.6	16
0	1013.9	0	-3.7	3	4.03	17	72	300	NW	2.6	1014.6	17	77	50	NE	1.5	1013.9	18
1.5	1013.6	1.7	?	1	1.48	16	72	300	NW	4.1	1013.9	17	82	?	?	1.5	1013.2	17
3.1	1013.6	0	11.2	3	2.48	17	72	300	NW	4.1	1014.6	19	73	?	?	4.1	1013.6	19
1.5	1014.9	2.7	-0.2	2	3.41	18	68	?	?	0	1015.3	17	82	?	?	1.5	1014.9	17
1.5	1015.3	0	?	6	4.41	18	68	270	W	2.6	1016	19	68	?	?	3.1	1015.3	?
1.5	1017.3	2	3.6	3	2.41	16	77	220	SW	5.1	1017	17	72	?	?	0	1017.3	18
2.6	1018	0	?	6	3.41	18	68	210	SW	6.2	1018.3	19	68	?	?	3.6	1017.6	20
2.1	1019.3	-4.7	8	1	1.45	16	77	240	SW	4.1	1019.7	14	88	?	?	0	1019	16
3.6	1019.7	0	1.2	3	2.45	16	77	250	W	4.1	1020.4	18	72	?	?	4.1	1019.3	19
0	1014.9	-3.7	8.5	1	0.58	18	77	140	SE	2.1	1015.3	17	88	?	?	0	1014.6	18
0	1014.9	0	0	2	1.58	18	77	220	SW	2.6	1015.3	18	88	?	?	1.5	1014.9	?
2.6	1011.2	-1	-4.4	1	0.85	?	?	340	N	4.1	1011.5	?	?	?	?	0	?	?
1.5	1011.5	-0.3	?	1	1.85	19	68	140	N	3.6	1011.9	18	88	360	N	2.6	1011.5	20
5.1	1010.5	5.5	0.3	1	0.83	19	68	180	S	5.1	1010.5	14	94	170	S	4.1	1010.2	18
?	?	?	?	?	1.83	?	?	?	?	?	?	?	?	?	?	?	?	?
3.6	1016.3	?	?	0	-0.58	18	68	270	W	2.6	1016.6	18	77	20	N	4.1	1016	18
0	1016.6	-0.3	0.9	?	?	20	60	280	W	4.1	1017	20	68	20	N	3.1	1016.3	20
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
1.5	1015.6	-2	5.9	?	?	17	72	350	N	2.6	1016.3	19	?	340	N	3.1	?	20
?	?	?	?	?	4.08	?	?	?	?	?	?	?	?	?	?	?	?	?
0	1013.2	0.4	-2.6	0	-0.17	16	77	260	W	5.7	1013.9	16	88	350	N	2.6	1013.6	?
1.5	1013.6	0	?	1	0.83	?	?	?	?	?	?	?	?	?	?	?	?	?
0	1013.9	3.1	-1.7	2	1.91	?	?	240	SW	4.1	1013.9	19	73	360	N	3.1	1013.2	20
1.5	1013.9	0	?	4	2.91	19	64	180	S	4.6	1014.3	19	68	80	E	2.6	1013.6	20
3.1	1017.3	1.7	-1.5	5	3.25	20	64	220	SW	5.1	1017.3	20	64	?	?	3.1	1016.6	20
3.1	1017.3	0	0.3	6	4.25	21	56	230	SW	5.1	1018	21	60	?	?	4.1	1017.6	?
?	?	?	?	?	3.48	?	?	?	?	?	?	?	?	?	?	?	?	?
1.5	1019	-0.3	4.4	4	4.48	?	?	?	?	?	?	20	78	20	N	2.6	1019	21
2.1	1019	-1.4	0.5	0	0.21	19	73	270	W	3.1	1019	17	88	310	NW	2.1	1018.7	19
?	?	?	?	?	1.21	?	?	?	?	?	?	?	?	?	?	?	?	?
?	?	?	?	?	0.88	?	?	?	?	?	?	?	?	?	?	?	?	?
3.6	1017.6	-0.3	2.5	4	1.88	?	?	?	?	?	?	?	?	?	?	?	?	19
1.5	1016.3	-0.7	0	1	2.58	20	78	270	W	4.1	1016.6	18	77	320	NW	2.6	1016.3	18
2.1	1016.6	0	11.9	4	3.58	20	78	290	W	4.1	1016.6	21	68	?	?	0	1016.6	21
4.6	1015.6	-1.7	-4.7	4	3.5	19	73	260	W	4.6	1016.3	23	57	350	N	4.1	1016	22
4.1	1015.6	0.4	-3.6	6	4.5	21	64	240	SW	2.6	1016	23	69	350	N	6.7	1015.6	23
2.6	1014.3	1.7	7.2	4	1.65	18	72	310	NW	3.6	1014.3	18	72	?	?	2.1	1013.6	18
2.6	1014.3	-0.4	10.2	6	2.65	19	68	220	SW	2.6	1014.6	20	68	?	?	2.1	1013.9	20
1.5	1016	3	1.9	2	1.58	19	73	240	SW	4.6	1016.3	16	82	?	?	1.5	1016	17
1.5	1017.3	-0.7	?	5	2.58	21	68	240	SW	4.6	1017.3	20	73	?	?	3.6	1017.3	21
0	1019	-2.4	0	1	2.58	19	73	270	W	3.1	1019.7	16	82	?	?	0	1019.3	18
2.6	1019.3	-0.3	3.1	4	3.58	19	73	260	W	2.1	1019.7	?	?	?	?	?	?	19
0	1016.6	-3.7	5.5	4	1.78	17	72	260	W	2.6	1017.3	17	72	?	?	0	1016.6	17
2.1	1017	0	14.4	5	2.78	18	72	250	W	3.6	1017.3	20	64	?	?	2.6	1017	19
2.1	1013.2	-0.3	?	2	1.79	21	64	240	SW	5.1	1013.6	19	77	300	NW	3.1	1012.9	20
3.1	1013.2	-0.3	-0.9	3	2.79	21	64	240	SW	5.1	1013.6	21	68	320	NW	4.6	1013.2	20
0	1009.9	-0.7	1.8	1	1	18	77	220	SW	4.1	1009.5	15	94	?	?	1.5	1009.2	15
0	1009.9	-0.4	6	2	2	18	77	220	SW	5.1	1009.9	17	82	?	?	1.5	1009.5	17
1.5	1011.5	-0.6	2.9	3	1.66	19	64	260	W	4.1	1011.9	17	77	?	?	0	1011.9	17
0	1011.9	-0.7	4.5	4	2.66	19	64	290	W	4.1	1011.9	19	68	280	W	2.6	1011.2	18
1.5	1020.4	0	-1.3	0	0.42	17	72	130	SE	4.1	1021	14	88	?	?	0	1020.4	16
0	1020.7	0	-7.5	2	1.42	17	72	120	SE	3.6	1021	18	72	?	?	0	1020.4	19
2.1	1013.2	-0.3	8.6	1	1.66	17	72	320	NW	2.1	1013.6	16	82	320	NW	3.1	1012.9	16
2.1	1013.2	-0.3	3.6	2	2.66	17	36	290	W	2.6	1013.6	17	77	?	?	1.5	1012.9	?
2.6	1019.7	0.3	5.1	2	4.58	?	?	?	?	?	?	?	?	?	?	?	?	?
3.1	1021.4	-0.4	6	2	5.58	21	64	250	W	5.1	1021.4	?	?	?	?	?	?	21
0	1014.9	0	-0.4	0	-0.42	18	68	340	N	4.1	1015.3	17	88	?	?	0	1014.9	18
2.6	1014.9	0.4	?	2	0.58	19	68	280	W	4.1	1015.6	18	83	?	?	0	1014.6	19
3.1	1013.2	0	?	3	1.66	19	73	180	S	4.1	1013.6	20	73	350	N	2.6	1012.9	19
2.6	1013.2	0.4	-11.7	4	2.66	21	64	230	SW	6.7	1014.3	20	73	10	N	3.6	1012.6	21
1.5	1016.6	-0.6	0.6	1	0.83	18	68	310	NW	2.6	1016.6	15	94	?	?	2.1	1016.6	18
2.6	1017	-0.7	-2.2	2	1.83	19	68	290	W	3.1	1017	17	82	290	W	1.5	1017	19
?	?	?	?	?	0.83	?	?	?	?	?	?	?	?	?	?	?	?	?
2.6	1015.6	-0.3	1.4	1	1.83	16	82	150	SE	4.1	1015.6	14	?	130	SE	3.6	1015.6	?
0	1020	0	-5.8	3	10.88	15	77	?	?	0	1020.4	14	82	?	?	0	1020.4	14
1.5	1019.7	0	?	3	11.88	?	?	?	?	?	?	?	?	?	?	?	?	?
1.5	1018.7	0.3	?	1	1.66	15	72	280	W	2.6	1019.7	16	72	360	N	3.1	1019	14
1.5	1018.7	0.3	?	2	2.66	15	77	?	?	0	1018.7	16	72	10	N	4.6	1019	17

Appendix B. Stratus burn-off training data set.

rhvRH	rhvWdd	rhvWdr	rhvWs	rhvP	sfoT	sfoRH	sfoWdd	sfoWdr	sfoWs	sfoP	sfodT	sfodt	sjcT	sjcRH	sjcWdd	sjcWdr	sjcWs	sjcP
?	?	?	?	?	19	88	300	NW	2.1	1017.3	2	5.4	20	83	?	?	0	1018.3
88	?	?	0	1018.7	19	88	?	?	0	1017.3	2	6.4	20	83	?	?	0	1018.7
77	130	SE	7.7	1008.5	14	82	280	W	1.5	1008.5	1	0.2	?	?	?	?	?	?
67	110	E	8.7	1008.8	15	77	?	?	1.5	1008.8	2	1.2	16	72	140	SE	6.7	1009.2
88	?	?	0	1014.6	13	88	280	W	4.1	1014.6	1	0.9	16	82	?	?	0	1014.6
82	310	NW	2.6	1014.9	13	88	270	W	5.7	1014.9	1	1.9	16	82	?	?	0	1014.9
59	280	W	4.1	1018.7	16	77	260	W	8.7	1017.6	3	2.9	17	68	?	?	2.1	1018.3
52	310	NW	4.1	1018.7	17	72	250	W	9.3	1018.3	4	3.9	19	56	350	N	4.1	1018.7
72	310	NW	4.1	1014.6	15	88	220	SW	3.1	1014.3	1	0.5	17	82	?	?	0	1014.6
68	310	NW	3.1	1014.6	17	77	240	SW	6.2	1014.3	3	1.5	18	72	330	NW	3.1	1014.6
72	?	?	0	1017.3	14	94	240	SW	6.7	1017.6	1	1.3	18	77	?	?	0	1017.3
?	?	?	?	?	16	82	240	SW	7.2	1017.6	3	2.3	20	68	360	N	4.1	1017.6
72	?	?	0	1015.3	16	82	?	?	0	1014.9	2	1.1	16	82	?	?	2.1	1015.3
64	?	?	0	1015.3	17	77	140	SE	3.1	1015.3	3	2.1	18	72	?	?	2.1	1015.3
77	?	?	0	1016.6	14	88	180	S	1.5	1016.3	1	1	12	88	260	W	2.6	1016.6
?	?	?	?	?	16	82	310	NW	2.1	1016.6	3	2	?	?	?	?	?	?
77	?	?	0	1018	15	88	300	NW	3.1	1017.6	2	2.2	17	88	?	?	0	1018
68	?	?	0	1018	16	82	320	NW	2.1	1018	3	3.2	18	83	?	?	0	1018
82	?	?	0	1014.6	13	94	250	W	4.6	1014.3	0	-0.2	16	82	360	N	2.1	1014.6
77	?	?	0	1014.6	14	88	220	SW	3.6	1014.6	1	0.8	16	82	?	?	2.1	1014.6
82	?	?	0	1011.9	14	88	280	W	3.1	1011.5	1	0.2	16	82	?	?	2.1	1011.9
82	?	?	4.1	1012.2	16	82	300	NW	3.1	1011.9	3	1.2	16	82	170	S	2.6	1012.2
88	?	?	0	1014.9	15	88	260	W	4.1	1014.3	2	3.5	17	82	130	SE	2.6	1014.9
72	?	?	2.6	1014.9	17	77	270	W	4.1	1014.3	4	4.5	16	88	?	?	2.1	1014.6
88	?	?	0	1014.6	15	82	180	S	1.5	1014.6	1	0.2	17	82	130	SE	2.6	1014.9
77	?	?	3.1	1014.6	16	82	?	?	0	1014.6	2	1.2	?	?	?	?	?	?
72	?	?	0	1012.6	14	94	?	?	1.5	1012.6	2	2.6	18	72	?	?	2.1	1012.9
72	?	?	0	1013.2	16	82	20	N	2.1	1012.9	4	3.6	18	77	?	?	2.1	1013.6
77	100	E	3.1	1013.9	15	82	160	S	2.6	1013.6	2	3.6	17	77	140	SE	5.1	1013.9
68	180	S	4.1	1014.3	17	72	160	S	4.6	1013.9	4	4.6	17	77	120	SE	4.1	1014.3
77	?	?	0	1013.9	16	77	230	SW	3.6	1013.9	2	1.1	18	77	?	?	0	1013.9
68	?	?	0	1014.3	16	77	290	W	5.1	1013.6	2	2.1	18	79	?	?	0	?
72	90	E	4.1	1015.3	16	82	180	S	3.1	1015.3	1	1.2	17	77	170	S	4.1	1015.3
?	?	?	?	?	17	77	320	NW	2.6	1015.3	2	2.2	19	73	200	S	3.1	1015.3
68	?	?	0	1017.6	15	88	210	SW	4.1	1017.6	1	0.6	17	77	180	S	4.1	1017.6
60	?	?	5.1	1018	16	82	220	SW	5.7	1018	2	1.6	19	68	170	S	2.6	1018.3
77	?	?	0	1019.7	15	88	240	SW	5.1	1019.3	1	-0.4	17	77	?	?	0	1020
64	?	?	3.1	1020	16	77	250	W	4.1	1019.7	2	0.6	?	?	?	?	?	?
77	?	?	0	1015.3	15	94	280	W	3.1	1014.6	1	0.1	18	83	?	?	0	1015.3
?	?	?	0	1015.3	16	88	?	?	0	1014.9	2	1.1	18	83	?	?	0	1015.3
?	190	S	2.6	?	16	88	?	?	0	1011.2	2	1.4	?	?	170	S	2.6	?
68	?	?	0	1012.2	18	77	80	E	2.1	1011.2	4	2.4	18	77	160	S	2.6	1011.9
72	130	SE	4.1	1011.2	18	77	170	S	6.2	1010.2	2	4	18	77	160	S	2.6	1010.5
?	?	?	?	?	19	73	170	S	7.7	1010.5	3	5	?	?	?	?	?	?
77	?	?	0	1016.6	17	77	?	?	7.6	1016	1	1	20	68	360	N	3.6	1016.6
64	?	?	0	1017	19	68	240	SW	2.1	1016.3	3	2	20	68	?	?	0	1017
?	?	?	?	?	16	?	270	W	3.6	?	2	1.7	?	?	?	?	?	?
?	?	?	?	?	17	82	280	W	4.6	1015.6	3	2.7	?	?	?	?	?	?
?	?	?	?	?	17	82	?	?	1.5	1018	2	1.8	?	?	?	?	?	?
?	?	?	?	?	18	83	120	SE	2.1	1018	3	2.8	?	?	?	?	?	?
73	?	?	0	1015.6	17	82	310	NW	3.6	1015.6	3	1.9	19	83	330	NW	2.1	1016.3
?	?	?	?	?	18	77	310	NW	3.1	1015.6	4	2.9	?	?	?	?	?	?
?	?	?	?	?	15	88	200	S	3.6	1013.6	1	0.8	18	77	?	?	0	1013.9
?	?	?	?	?	16	82	240	SW	3.6	1013.6	2	1.8	?	?	?	?	?	?
64	140	SE	6.2	1014.3	18	77	190	S	4.1	1013.6	2	1.8	17	82	140	SE	3.6	1014.6
64	170	S	5.1	1014.6	18	77	160	S	5.1	1013.9	2	2.8	19	73	190	S	5.1	1014.6
60	?	?	0	1018	19	68	220	SW	5.7	1017	3	4	19	68	?	?	0	1017.6
?	?	?	?	?	21	60	250	W	4.1	1017.3	5	5	21	60	?	?	0	1018
?	?	?	?	?	19	88	220	SW	3.6	1019	2	1.7	?	?	?	?	?	?
68	300	NW	4.1	1019.7	20	83	270	W	3.1	1018.7	3	2.8	20	78	?	?	0	1019.7
83	310	NW	5.1	1019.3	18	94	280	W	2.6	1019	0	-0.4	21	78	310	NW	3.6	1019.3
?	?	?	?	?	19	88	280	W	3.6	1019.3	1	0.6	?	?	?	?	?	?
?	?	?	?	?	18	88	270	W	4.1	1017.6	1	0.6	?	?	?	?	?	?
73	?	?	3.6	1018.3	19	77	270	W	5.7	1017.3	2	1.6	19	77	310	NW	3.1	1018.3
77	?	?	0	1017	19	88	290	W	2.1	1016	1	0.1	17	88	?	?	0	1017
68	?	?	0	1017.3	19	88	280	W	4.1	1016.6	1	1.1	19	83	?	?	0	1017.3
60	330	NW	5.1	1015.6	18	88	240	SW	4.6	1015.6	1	4.8	21	68	300	NW	2.6	1015.6
57	310	NW	4.1	1015.6	19	83	230	SW	5.7	1016	2	5.8	22	64	330	NW	3.6	1015.6
72	?	?	0	1014.6	17	88	250	W	5.7	1013.9	0	-0.3	17	77	?	?	2.1	1014.3
68	?	?	2.6	1014.3	18	88	260	W	6.2	1013.9	1	0.8	18	77	320	NW	2.6	1013.9
72	?	?	0	1015.6	18	88	230	SW	3.1	1016	1	2.8	18	77	?	?	0	1016.3
64	?	?	0	1017	19	83	230	SW	4.1	1016.6	2	3.8	20	68	?	?	0	1017.3
77	320	NW	2.6	1020	18	83	270	W	3.1	1019	1	0.6	18	83	?	?	0	1019.7
73	320	NW	2.6	1020	19	77	270	W	2.6	1019	2	1.6	18	77	?	?	0	1019.7
77	310	NW	2.1	1017	16	88	230	SW	6.7	1016.6	0	-0.1	16	82	310	NW	2.1	1017
68	310	NW	4.1	1017	17	82	270	W	5.1	1017	1	0.8	18	72	350	N	3.6	1017
73	310	NW	4.1	1012.9	18	83	250	W	5.1	1012.9	0	-0.1	19	77	310	NW	4.1	1013.2
68	290	W	5.1	1013.6	20	73	240	SW	5.7	1012.9	2	0.9	20	68	360	N	4.1	1013.6
82	?	?	0	1010.2	17	82	250	W	3.1	1009.2	0	-1.5	16	88	?	?	0	1009.9
77	?	?	0	1010.2	17	82	250	W	5.1	1009.5	0	-0.5	16	88	180	S	2.1	1011.5
77	?	?	0	1011.9	18	72	240	SW	5.1	1010.9	1	0.1	19	73	?	?	2.1	1011.9
72	?	?	0	1012.2	18	72	240	SW	5.1	1011.2	1	1.1	?	?	?	?	?	?
77	?	?	0	1020.7	15	88	140	SE	2.1	1020.4	2	1.8	18	77	?	?	0	1021
68	?	?	0	1020.7	16	82	140	SE	2.6	1020.7	3	2.8	20	68	?	?	0	1020.7
82	360	N	2.1	1013.2	15	88	290	W	3.1	1012.9	1	1.2	18	77	?	?	0	1013.2
?	?	?	?	?	16	82	280	W	2.6	1012.9	2	2.2	19	73	?	?	0	1013.2
?	?	?	?	?	18	88	270	W	4.6	1020	1	0.5	?	?	?	?	?	?
68	300	NW	4.1	1020.7	19	77	270	W	5.7	1021	2	1.5	22	69	360	N	3.6	1021
72	?	?	0	1014.9	15	82	210	SW	2.1	1014.9	?	?	?	?	?	?	?	?
68	?	?	0	1014.9	?	?	?	?	1.5	1015.3	?	?	?	?	?	?	?	?
68	?	?	0	1012.9	18	77	190	S	6.2	1013.2	2	6.4	20	68	?	?	0	1013.6
64	?	?	0	1013.2	18	77	190	S	4.6	1013.6	2	7.4	23	57	?	?	0	1013.2
72	?	?	0	1016.6	17	82	320	NW	2.1	1016	3	1.1	?	?	?	?	?	?
68	320	NW	4.1	1016.6	18	77	?	?	0	1016.3	4	2.1	19	77	?	?	0	1017
?	?	?	?	?	14	94	150	SE	2.6	1014.6	1	3.5	?	?	?	?	?	?
?	?	?	0	1015.6	14	94	150	SE	2.1	1015.3	1	4.5	16	?	130	SE	1.5	?
82	?	?	0	1020	13	88	170	S	2.1	1020	2	8.3	16	77	?	?	1.5	1020
?	?	?	?	?	14	88	?	?	2.1	1019.7	3	9.3	16	82	?	?	0	1020
82	350	N	2.6	1019	13	94	270	W	4.6	1019	1	8.2	16	77	?	?	0	1019.3
68	?	?	2.1	1019.3	14	82	310	NW	2.6	1019	2	9.2	16	77	340	N	3.1	1019.3

Appendix B. Stratus burn-off training data set.

smwT	smwRH	smwP	smwdP	sqlT	sqlTd	sqlWdd	sqlWdr	sqlWs	sqlTA	sqldT	sqldt	tamT	tamWdd	tamWdr	tamWs	tamTA	cond
20	58	1017.3	0	18.1	15.7	151	SE	2.2	-3.7	0.9	3.9	13.7	324	NW	4.6	-14	str
20	58	1017.3	0	18	15.6	162	S	3.1	-2.7	0.8	4.9	15.6	323	NW	6.1	-20.7	bo
15	45	1008.5	0	13.3	10.9	0	N	2.2	0.1	1	0.8	12.8	226	SW	2	1.4	str
16.1	48	1008.8	0	14.1	10.7	279	W	3.5	7	1.8	1.8	11.5	157	SE	1.5	?	bo
15	49	1014.2	0.4	14.4	11.4	250	W	2.8	3	1	1.2	20.4	321	NW	5.1	14.8	str
15.6	56	1014.6	0.3	15.1	11.1	288	W	4.5	0.3	1.7	2.3	21	317	NW	3.6	0	bo
17.8	25	1018	-0.4	16.4	9.9	290	W	8	2.1	3.3	5.5	13.4	309	NW	5.1	-2	str
18.9	41	1018.3	0	17.6	10.5	283	W	6.3	-0.7	4.5	6.5	14.3	310	NW	5.6	-6.7	bo
17.2	47	1014.2	0.1	16.3	13.1	292	W	5.8	-7.2	2.1	4.4	25.7	295	NW	2	6.3	str
18.3	54	1014.2	0.1	17.8	13.3	285	W	6.9	-3.4	3.6	5.4	26.4	296	NW	2	-9.1	bo
16.7	47	1017.3	0.3	15.8	12.6	282	W	8	3.7	2	3.7	21.3	312	NW	5.1	29.1	str
17.8	54	1017.6	0	17.4	13.1	276	W	6.2	-3.9	3.6	4.7	21.8	313	NW	5.6	25.6	bo
16.7	49	1014.9	0	15.9	13.6	21	N	2.5	0.1	0.9	4.3	20.7	327	NW	3.6	16.8	str
17.2	53	1014.9	0.4	16.5	13.2	302	NW	2.9	3	1.5	5.3	23.2	346	N	1.5	27.6	bo
16.1	51	1016.3	0	15.3	12.4	337	NW	2.6	-4.4	0.7	1.2	20.1	187	S	2.5	-3.5	str
16.7	56	1016.3	0.3	16.1	13.2	17	N	2.3	0.1	1.5	2.2	23.9	196	S	2	-16.3	bo
17.2	51	1017.6	0	15.8	13.5	63	NE	2.6	3.2	0.9	1.7	24.9	274	W	1	-28.7	str
17.2	59	1018	0	16.7	14	68	E	2.1	2.1	1.8	2.7	27	215	SW	1.5	-27.6	bo
16.1	70	1014.2	0.1	14.7	11.4	187	S	2.7	6.3	0.7	0.3	17	68	E	1	-6	str
16.1	54	1014.6	0	16	11.6	65	NE	1.5	0.9	2	2	18	44	NE	1.5	3.5	bo
16.1	70	1011.5	0	15.4	12.7	29	NE	1.4	3.2	1.1	-0.3	22.3	321	NW	4.1	14.6	str
17.2	50	1011.9	0	15.9	13.1	346	N	2.3	-0.1	1.6	1.8	22.9	343	N	4.1	6.3	bo
16.7	69	1014.2	0.1	16.9	13	263	W	2.1	2.2	2.3	1.3	24.1	311	NW	3.6	14.2	str
18.3	51	1014.2	0.1	17.4	14.3	71	E	3.4	1.9	2.8	3.2	25.9	309	NW	3.1	4	bo
16.7	67	1014.2	0.4	15.7	13.1	360	N	2.4	-1.8	0.9	-0.1	23.9	292	W	3.1	34.5	str
17.2	53	1014.6	0	16.2	15	20	N	2	0	1.4	7.9	25.2	310	NW	2	0	bo
16.1	70	1012.5	0.1	15	13.3	354	N	2.4	?	0.8	1	25.3	305	NW	2.5	?	str
17.2	52	1012.9	0	15.7	13.6	354	N	2.5	0.3	1.5	4.9	25.1	292	W	1.5	2.1	bo
17.2	60	1013.2	0.4	15.9	11.8	277	W	2.9	-4.2	0.7	-0.3	10.4	199	S	3.6	-2.5	str
17.8	45	1013.9	0	16.7	11.8	246	SW	1.8	1.4	1.5	3.4	17	235	SW	2	0	bo
17.8	65	1013.5	0.4	16.3	13.5	47	NE	2.8	0.2	1.4	0.5	23.7	196	S	1	0.5	str
17.8	50	1013.9	-0.3	17.1	13.7	16	N	2.4	4	2.2	3.6	24.2	188	S	1	-35.8	bo
17.8	63	1014.9	0.4	16.2	12.6	281	W	1.9	-0.7	0.6	-0.3	20	58	NE	1	9.6	str
18.3	47	1015.2	0.1	16.6	12.6	358	N	3	-1	1	3	19.8	22	N	1	-7.3	bo
17.8	65	1017.6	0	16.7	12.6	274	W	3.3	-5.9	2.4	1	17.2	320	NW	3.6	11.2	str
17.8	48	1018	0	16.7	12.6	280	W	5.3	-3.3	2.4	4.3	17.8	313	NW	2.5	6.4	bo
16.7	67	1019.3	0	15.5	12.1	144	SE	2.4	2	2.1	2	18.6	313	NW	3.1	8.2	str
17.8	48	1019.6	0.1	16.7	12.3	305	NW	2.6	-0.5	3.3	6	19.6	318	NW	3.6	8.1	bo
16.7	75	1014.6	0	15.9	14.4	144	SE	3.1	5.1	0.9	-0.5	26.1	342	N	2.5	-0.1	str
17.8	59	1014.9	0	16.8	14.8	139	SE	2.7	2.1	1.8	3.8	26	351	N	2	0	bo
17.8	67	1010.8	0.4	16.9	14.2	5	N	1.4	-0.8	1.5	-0.6	19.1	186	S	6.1	-13.4	str
18.3	53	1011.2	0	17.4	14.5	98	E	1.3	0.1	2	3.7	20	188	S	6.1	-6.3	bo
19.4	58	1010.2	0	18.1	12.9	142	SE	2.5	-0.2	2.1	-1.3	11.7	177	S	12.8	31.1	str
20.6	40	1010.5	0	19.1	12.6	169	S	5.9	-0.1	3.1	4.6	11.7	174	S	12.2	25.5	bo
19.4	57	1015.9	0.1	17.9	12.6	262	W	1.7	?	0.7	-1.9	17.8	347	N	7.5	?	str
20	43	1016.3	0	18.8	13.1	212	SW	1.7	-0.2	1.6	2.4	14.3	356	N	2	1.5	bo
17.8	70	1015.6	?	17	13.9	351	N	3.1	0.3	1.4	0.3	20.7	18	N	1	-10.6	str
18.3	53	1015.2	0.4	17.5	14.2	59	NE	1.6	2.2	1.9	5.5	22.1	68	E	1	-17.7	bo
18.3	67	1018	0	16.7	14	121	SE	3.1	?	1.5	0.6	23.7	4	N	1.5	?	str
19.4	50	1018	0	17.7	14.4	108	E	3.6	-0.4	2.5	4.1	24	354	N	1	11.8	bo
17.2	75	1015.6	0	17.1	14.6	30	NE	2.1	0.3	1.8	1.7	26.8	303	NW	2.5	-11.3	str
17.8	61	1015.6	0	18.4	15	?	?	3.3	?	3.1	3.2	28.2	294	NW	2	-31	bo
16.7	67	1013.2	0.4	15.8	12.6	246	SW	2.4	-1.9	0.8	-0.3	23.3	323	NW	4.6	53.5	str
17.8	50	1013.2	0.4	16.5	13.3	98	E	1.6	1.2	1.5	2.3	23.5	330	NW	4.6	29.9	bo
18.9	63	1013.5	0.1	17.4	12.7	101	E	2.1	0.2	3.4	1.8	11.1	177	S	5.6	12.7	str
20	44	1013.5	0.4	19.3	13.4	146	SE	2.2	-3.1	5.3	3.4	10.9	170	S	5.1	-2.6	bo
21.1	55	1016.9	0.1	19	12.2	251	W	4.4	0	5	3.2	13.8	284	W	3.1	-18.5	str
21.7	35	1017.3	0	20.5	12.6	218	SW	4	-1	6.5	4.4	13.7	245	SW	2	9.7	bo
20	68	1019	0	18.8	15.7	217	SW	1.8	0	3.4	2	16.7	249	W	1.5	-2.6	str
21.1	50	1019	-0.3	20.2	15.6	291	W	3.9	-0.3	4.8	6.8	19.1	338	N	2	1.8	bo
20	65	1018.6	0.4	18.1	15.2	306	NW	2.2	0	0.5	-3.5	12.1	327	NW	3.1	-6.6	str
20.6	52	1019	0.3	19.3	15.5	115	SE	1.6	1.4	1.7	1.6	13.4	316	NW	3.1	-2.1	bo
18.9	68	1017.6	0	16.9	14.8	221	SW	1.9	-3.4	2.4	0.3	13.8	319	NW	4.6	-8.5	str
20	48	1017.3	0	19.5	14.9	271	W	3.2	0.9	5	2	14.6	324	NW	2	15.8	bo
18.9	70	1015.9	0.1	18	15.7	118	SE	2.1	-4	3	-0.5	13.4	291	W	4.1	-9.8	str
20.6	54	1016.3	0.3	21.2	16.5	133	SE	1.7	11.4	6.2	4.7	15.1	290	W	4.1	-1.6	bo
20.6	63	1015.6	0	20.7	14.6	233	SW	5.1	1.2	3.9	0.6	18.5	342	N	2	-0.4	str
21.1	51	1015.6	0.4	23.5	15.2	227	SW	3.4	2.2	6.7	4.8	19.4	345	N	2	0	bo
20	61	1013.9	0	18.7	14.2	235	SW	4.9	2.7	3.3	0.2	18.1	311	NW	3.6	1.9	str
20	49	1013.9	0	19.7	14.1	260	W	5.2	1	4.3	3.3	18.3	317	NW	3.6	0.2	bo
19.4	68	1015.9	0.1	20.1	15.6	240	SW	4.3	-1.9	3.7	-0.9	19.5	299	NW	2	2.9	str
20.6	47	1016.6	0	19.3	14.6	293	NW	5.1	-1.3	2.9	7.8	19.4	299	NW	3.1	1.2	bo
19.4	65	1019	0	16.7	14.3	190	S	2	-4.4	1	-1.2	19.5	281	W	1	-1.8	str
20	48	1019	0	19.1	14.8	278	W	1.8	0	3.4	2.9	21.7	97	E	1	-6.4	bo
18.3	65	1016.6	0	18.1	13.4	274	W	4.7	-5.8	3.1	0.7	20.4	315	NW	2.5	11.5	str
18.9	49	1016.6	0.4	19.2	13.6	261	W	4.8	1.7	4.2	4.3	22.4	312	NW	2.5	-4	bo
20.6	63	1012.9	0	18.9	14.7	289	W	3	-0.3	0.1	-2.9	15.8	340	N	4.1	-4.9	str
20.6	47	1013.2	-0.3	19.5	14.5	306	NW	4.5	1.4	0.7	0.6	19.7	?	?	2	?	bo
17.8	70	1009.1	0.1	16.6	14.2	233	SW	3.4	-0.3	0	-2.7	18.3	301	NW	3.1	2.5	str
18.9	50	1009.5	0	18	14.5	238	SW	3.2	1.5	1.4	7.3	23.1	267	W	1	-6.5	bo
18.9	60	1010.8	0.1	17.6	13.1	239	SW	4.2	-0.1	?	?	16.9	292	W	3.6	-2.6	str
20.6	57	1011.5	-0.3	19.4	13.7	261	W	4.9	-2.1	?	?	15.5	304	NW	4.1	-7.8	bo
16.1	70	1020.3	0.1	15	13	130	SE	2.6	0	0	-0.7	13.1	332	NW	3.1	-9.8	str
17.8	51	1020.3	0.4	17.5	13	245	SW	4.4	-6.4	2.3	4.7	13.3	343	N	3.6	-16	bo
16.7	67	1012.9	0	15.1	12.4	300	NW	2.2	0.1	0.9	1.4	27.8	12	N	1.5	-21.9	str
17.2	52	1012.9	0	15.5	12.5	14	N	2	-0.6	1.3	6.8	28.8	23	NE	1.5	-16.1	bo
19.4	70	1020	0	18.2	15.2	320	NW	4.1	-0.1	1.6	-0.1	16.3	329	NW	3.1	-0.3	str
20.6	46	1021	0	18.7	15.5	282	W	3.8	-0.3	2.1	5.8	17.3	324	NW	3.6	0	bo
17.8	67	1014.6	0.3	16	13.9	79	E	2.8	1.2	2.1	1.6	18.1	176	S	6.6	-14.4	str
18.3	50	1014.9	0.4	16.7	14.2	49	NE	2.7	?	2.8	3.9	19.5	180	S	5.6	?	bo
19.4	68	1012.9	0.3	17.9	14.7	71	E	2.2	0.2	3.3	2	11.8	180	S	6.6	6.6	str
20.6	51	1013.2	0.4	20.3	14.1	167	S	2.8	-0.3	5.7	3	12.1	178	S	6.6	13.3	bo
17.8	70	1015.9	0.1	16	13.5	302	NW	2.5	0.4	2	1.8	12.4	338	N	3.6	-6.2	str
18.3	53	1016.3	0	17.1	13.7	303	NW	2	1.8	3.1	2.8	14.1	347	N	3.1	-10.9	bo
15.6	72	1014.2	0.4	13.8	12.8	183	S	2.5	0.2	0.7	1.7	11.1	319	NW	2.5	-14.7	str
16.1	57	1014.9	0.4	14.1	13	114	SE	2.9	0.1	1	3.4	11.9	305	NW	2	-8.4	bo
16.1	64	1019.6	0.4	13.2	11	179	S	1.9	-0.1	2.3	5.9	19.7	3	N	4.6	35.2	str
16.7	47	1019.6	0.1	14.2	11.4	76	E	1.9	?	3.3	9	20.4	341	N	4.6	?	bo
15.6	64	1019	0	13.3	10.6	284	W	1.5	0.6	1.4	5.7	23.6	328	NW	2.5	-4.4	str
16.1	49	1019	0	14.6	11.2	266	W	2.2	0.6	2.7	9.1	26.3	145	SE	1.5	-49.8	bo

Appendix C. Attribute selection and forecast accuracy related to data availability.

Attribute	% of case data missing	Attribute applied to forecast STR and BO
JulDate	0%	x
TimeZ	0%	x
VVVeta	3%	
LIeta	3%	
VVVngm	3%	
LIngm	3%	
sfoInHt	1%	x
sfoInSt	1%	
sqlInHt	33%	
sqlInSt	33%	x
sfoCld%	9%	
sfoCldBs	9%	x
sqlCld%	26%	
sqlCldBs	26%	
SolAng	0%	
sfoRad	17%	
sqlRad	18%	
funT	5%	
funTd	5%	
funWdd	5%	
funWdr	5%	
funWs	6%	
funTA	12%	
fundT	6%	x
fundt	4%	
hwdT	19%	
hwdRH	22%	
hwdWdd	41%	
hwdWdr	41%	
hwdWs	19%	
hwdP	24%	
hwddP	24%	
hwdTA	25%	
nuqT	19%	
nuqRH	19%	x
nuqWdd	52%	
nuqWdr	52%	
nuqWs	19%	
nuqP	19%	
nuqdP	19%	
nuqTA	40%	
nuqdT	22%	x
nuqdt	19%	
oakT	19%	
oakRH	25%	
oakWdd	23%	
oakWdr	24%	
oakWs	18%	
oakP	24%	
paoT	20%	
paoRH	27%	
paoWdd	52%	
paoWdr	52%	
paoWs	20%	
paoP	26%	
rhvT	25%	
rhvRH	31%	
rhvWdd	68%	
rhvWdr	68%	
rhvWs	22%	
rhvP	28%	
sfoT	2%	
sfoRH	3%	
sfoWdd	16%	

Case Date	MSI stratus clearing time (the @45 time), GMT	% of attribute data missing for the STR condition	STR case missed by DT	STR case missed by RS	% of attribute data missing for the BO condition	BO case missed by DT	BO case missed by RS
96148	1448	61%			50%	x	x
96150	1745	42%			42%		
96167	1850	42%			41%		
96172	1939	46%			39%	x	x
96173	1735	42%			41%		
96176	1945	86%		x	78%		
96177	2108	42%			43%		
96186	1545	35%		x	27%	x	
96189	1636	24%		x	30%		
96190	1735	28%		x	25%		
96191	1710	20%		x	52%		
96192	1820	43%	x	x	24%		
96193	1645	37%		x	89%		
96195	1618	36%		x	25%	x	
96196	1725	23%			40%	x	
96197	1805	22%			42%	x	
96204	1624	21%		x	23%		
96205	1655	10%		x	12%		
96206	1745	26%	x	x	11%		
96207	1740	24%			23%		
96208	1820	7%			8%		
96220	1930	4%			4%		
96221	1741	37%			12%		
96228	1810	27%			50%		
96230	1750	52%			48%		
96233	1639	45%			39%	x	x
96235	1635	30%			25%		
96237	1832	10%			14%		
96238	1834	28%			2%		
96239	1920	36%			10%		
96240	1615	7%			7%		
96246	1722	2%			7%		
96247	1907	12%			7%		
96255	2227	23%			2%		
96257	1822	11%			3%		
96259	2155	2%			11%		
96267	1800	13%			15%		
96268	1710	9%			13%		
96269	1929	9%			17%		
96270	1922	23%			10%		
96271	1925	41%			12%		
96272	1852	7%			14%		
96273	1905	11%			13%		
96274	2208	5%			52%		
96275	2147	10%			22%	x	x
96276	1943	10%			57%		
96277	1805	21%			14%		
97130	1845	12%			2%		
97131	1835	9%			14%		
97132	1630	13%			14%		
97134	1628	7%			8%		x
97143	2050	2%			7%		
97147	1400	35%			38%	x	x
97151	1436	30%			13%	x	x
97159	1615	11%			10%		
97168	1618	9%			4%		
97179	1938	9%			7%		
97185	1800	8%			5%		
97186	1820	9%	x	x	15%		
97194	1653	13%			13%		
97195	1655	4%			41%		
97196	1650	13%			11%		
97199	1619	7%			7%		
97200	1600	4%			5%		

Appendix C. Attribute selection and forecast accuracy related to data availability.

Attribute	% of case data missing	Attribute applied to forecast STR and BO
sfoWdr	16%	
sfoWs	1%	
sfoP	2%	
sfodT	3%	
sfodt	3%	x
sjcT	21%	
sjcRH	28%	
sjcWdd	66%	
sjcWdr	66%	
sjcWs	21%	
sjcP	28%	
smwT	13%	
smwRH	18%	x
smwP	18%	
smwdP	19%	
sqlT	16%	
sqlTd	16%	
sqlWdd	17%	
sqlWdr	17%	
sqlWs	16%	
sqlTA	23%	
sqldT	17%	
sqldt	17%	
tamT	1%	
tamWdd	2%	
tamWdr	2%	
tamWs	1%	
tamTA	9%	
Average:	19.6%	10

Case Date	MSI stratus clearing time (the @45 time), GMT	% of attribute data missing for the STR condition	STR case missed by DT	STR case missed by RS	% of attribute data missing for the BO condition	BO case missed by DT	BO case missed by RS
97201	1751	9%			4%		
97202	1645	10%			13%		
97207	1713	12%			9%		
97208	1657	0%			4%		
97209	1724	10%			10%		
97210	1720	4%			12%		
97211	1720	7%			8%		
97212	1722	7%			11%		
97218	1630	11%			15%		
97220	1646	22%			5%		
97221	1645	0%			48%		
97223	1720	13%			7%		
97224	1752	53%			50%		
97225	1745	53%			48%		
97226	1900	4%			51%		
97227	1645	11%			40%		x
97228	1750	4%			3%		
97229	1910	7%	x	x	11%		
97235	1924	47%			9%		
97236	1608	4%			50%		
97237	1648	47%			26%		
97238	1630	7%			7%		
97241	1925	0%			0%		
97242	1734	7%			4%		
97245	1730	7%			12%		
97246	1630	9%			11%		
97250	1742	4%			2%		
97254	1752	3%			3%		
97255	1555	9%			9%	x	x
97256	1735	12%			13%		
97258	1630	12%			12%		
97265	1735	4%			13%		
97269	1830	43%			11%		
97273	1730	20%			23%		
97274	1835	8%			4%		
97275	1745	13%			9%		
97282	1645	49%			8%		
97294	1848	13%			41%		
97295	1935	8%			10%		
Stats.	Avg: 1763Z	Avg: 19.0%	Tot: 4	Tot: 13	Avg: 20.3%	Tot: 11	Tot: 9

Appendix D. Equations for solar altitude angle and relative humidity.

Solar altitude angle, β (computed using Sun Position shareware from Seattle Energy Works):

$$\beta = \sin^{-1}\{[\cos(\text{latitude})*\cos(\sigma)*\cos(H)]+[\sin(\text{latitude})*\sin(\sigma)]\} \quad (1)$$

σ = declination angle

$$= 23.45*\sin[360/365*(284+\text{day of year})] \quad (2)$$

H = hour angle

$$= (\text{minutes before noon})/4, \quad (3)$$

Relative humidity, RH:

$$RH = (q/q_S)*100 \quad (4)$$

$$q_S = 0.622*e_S/(P-0.378*e_S) \quad (5)$$

$$e_S = 6.11*\exp(a*(T-273.16)/(T-b) \quad (6)$$

P = barometric pressure (mb)

a = 17.26

T = temperature (°K)

b = 35.86

$$q = 0.622*e/(P-0.378*e) \quad (7)$$

$$e = 6.11*\exp(a*(Td-273.16)/(Td-b) \quad (8)$$

Td = dewpoint temperature (°K),